

Robot Navigation Techniques for Engineering Drawing Analysis

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Abstract

Engineering drawings provide a significant challenge to image analysis. The goal is to take a scanned engineering drawing image and produce an interpretation of the contents in terms of characters, digits, arrows, line segments, dimensions, etc. Our goal is to incorporate these results into a legacy system re-engineering process (e.g., image analysis must provide parameter values for manufacturing features like counterbore holes, etc.). We propose to treat the problem in two steps: (1) determine a good set of feasible points which constitute the markings on the page, and (2) subsequently treat these as a 2D floor plan that is explored by a tiny mobile agent that navigates through the drawing and produces a map. The trajectories followed by the agents allow a segmentation of the image into basic geometric units: straight line segments, end points, branch points, etc. In this paper we study static Pseudo-Range Maps (PRMs) to identify point features in the image.

We believe that this approach can be applied to any kind of line drawing material where the objects of interest can be segmented. We conjecture that it will also be possible to characterize and identify processes that create such line drawings (e.g., people, printers, etc.).

1 Introduction

Almost all legacy engineering designs involve 2D CAD drawings. The most common tasks for the re-engineering of legacy systems include the modification of existing designs to make a new design, or the synthesis of 3D models from multiple 2D views (usually available as engineering drawings). Automatic engineering drawing analysis offers a useful tool in the interpretation of engineering drawings when the original electronic CAD is not available. Engineers engaged in reverse engineering rely heavily on the scanned engineering drawings from blueprints as well as 3D data from the available

physical parts. Our goal is to aid the design process by achieving the most accurate image segmentation possible in order to permit the best interpretation of annotations in digitized images of CAD drawings.

The automatic analysis of engineering drawings has posed interesting and challenging research topics in document analysis, pattern recognition, image processing and computer vision for a few decades [19, 22–25]; however, the complete analysis of engineering drawings is still an unsolved problem. Most extant systems exhibit brittle performance when applied to real world image sets. (See Tombre [1] for an overview of the field and Kanungo et al. [2] for insightful commentary.) Most previous work deals with the interpretation of particular symbols and structures in CAD drawings (e.g., straight line vectorization [4, 12, 16], arcs [20], and dimensioning analysis [3, 5]). Our survey shows that previous research focuses on methodologies and algorithms for individual aspects of the problem and only achieves good overall performance in special circumstances. Most of the known algorithms and procedures require noise-free conditions which is usually an unrealistic assumption. Research is still underway in this area due to real world application demand, and no existing system works well universally.

We have studied this problem for a number of years (e.g., see [8–11, 22]). That work explored the use of structural constraints in the underlying document elements, and feedback mechanisms to reinforce paths to successful interpretations. However, one constant issue is the poor quality of the image segmentation of the engineering drawings.

We propose to improve the image segmentation process by taking advantage of the fact that engineering drawings are human artifacts and thus have a regular structure. Moreover, this structure is quite similar in nature to the 2D floor plan of a building layout; e.g., lines are like hallways. Figure 1 shows a typical layout to be explored and mapped by a mobile robot. Similarly, the scanned digital image of an

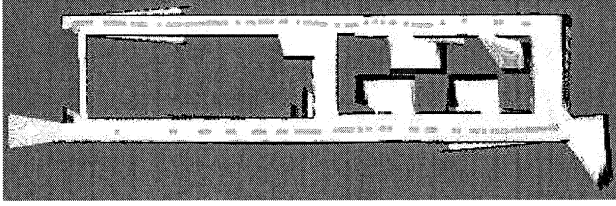


Figure 1: Building Layout for Mobile Robot Mapping

engineering drawing has errors and noise, and therefore poses difficulties for standard image processing techniques. We propose a paradigm shift: view the drawn lines and symbols as hallways, rooms, etc., and use robot navigation and mapping methods to analyze the drawing structure. Mobile agents are placed “inside” the drawn lines and located with subpixel precision. The gray levels serve as a *density* function, and a pseudo-range scan can be performed at any pixel (the background of the line drawing image serves as the solid surfaces). The engineering drawing analysis is now defined as a robot mapping problem. We propose to demonstrate that features important to the drawing analysis can be extracted using this approach. Once these features can be robustly extracted, we believe that it is possible to obtain the line segments and structures necessary for high-quality drawing interpretation. The method also makes it possible to learn interesting structure within the image automatically. Finally, localization methods can be used to match models of known structures (e.g., letters, digits, arrowheads, etc.).

In this paper we explore the static use of pseudo-range maps at individual pixel locations to classify 0-dimensional features (i.e., point features), including: (1) *end points*, (2) *interior corridor points*, (3) *corner points*, and (4) *branch points*. Performance of this approach is demonstrated on engineering drawing images for which ground truth is available.

2 Method

We propose a two-step process:

1. Threshold the image into foreground and background components, and
2. Use mobile robot mapping techniques to interpret point features in the foreground data.

Thus, step 1 produces a binary image and step 2 extracts point features of interest.

2.1 Foreground Segmentation

The images being analyzed are mostly comprised of lines; that is, elongated, thin linear structures. The foreground segmentation algorithm takes as input an image, I , and a length, k and is given as follows:

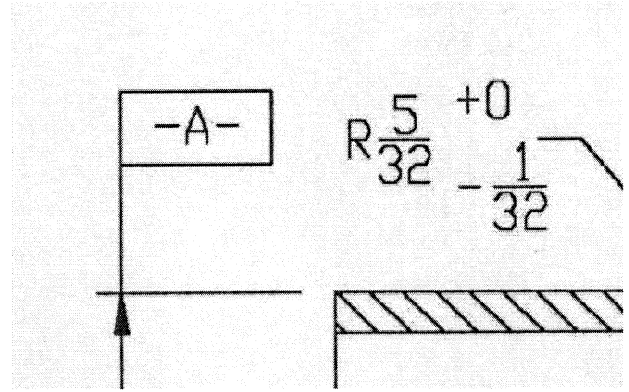


Figure 2: Original Gray Level Drawing Image.

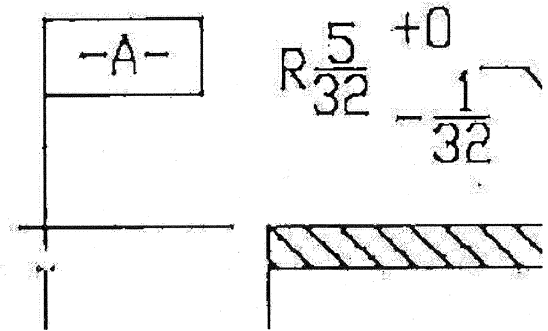


Figure 3: Segmented Image.

- for every pixel, p , in I
 - analyze the linear vector of k pixels centered at p and in the 4 major orientations (0, 45, 90, 135 degrees)
 - pick the orientation, if any, with the strongest contrast between the middle pixels and the outer pixels (outer pixels higher valued than the middle pixels since the drawing is dark on light background).

Figure 2 shows an original gray level image and Figure 3 its segmented counterpart. (Figure 4 shows a segmented image using a standard within-group variance thresholding technique [18].)

Note that the arrow head is missing in Figure 3 as it is not a linear structure. Also note how the fraction numbers and line are messy and not well-separated in Figure 4.

2.2 Mobile Robot Mapping Techniques

Figure 5 shows part of an engineering drawing with the position and orientation of a mobile agent overlaid on it. The agent can produce a pseudo-range map (PRM) at any location; Figure 6 shows the

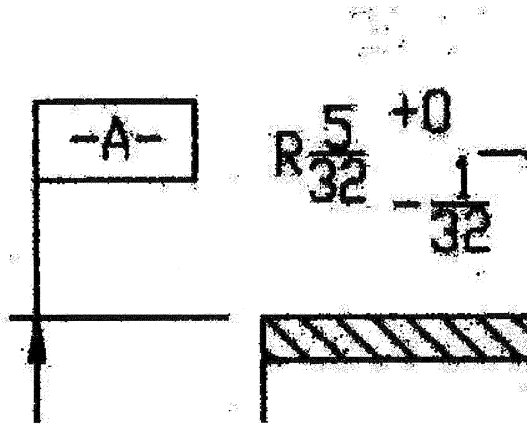


Figure 4: Image Segmented using Standard Method.

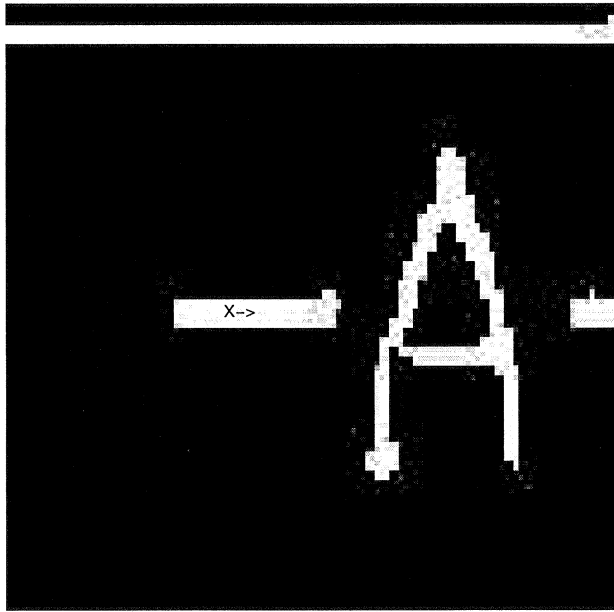


Figure 5: An Engineering Drawing with Agent Overlaid.

PRM for the given location (note that the range is taken at sub-pixel accuracy). The basic idea is that the agent will use the PRM in order to explore the line drawing. This will be done using standard mapping techniques. While exploring the line drawing, features, segments and symbols will be extracted. Performance will be analyzed using a dataset for which we have determined the ground truth.

Mobile robot navigation, localization and mapping is still an area of active research in the robotics community [2, 17]. However, many techniques are already developed which apply to our problem domain[7].

Mobile robot mapping techniques exploit three types of map concepts: *topological*, *geometrical*, and *grids*. From one or more of these standpoints, a map of the domain will be built. Specific approaches in-

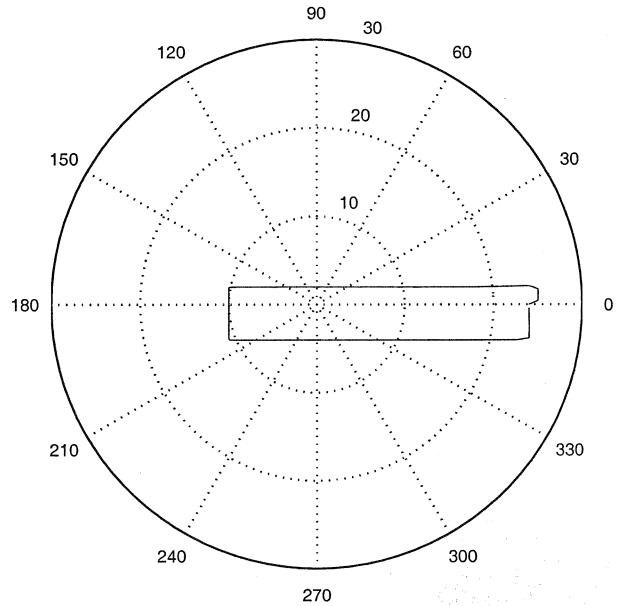


Figure 6: A Pseudo-Range Map (PRM) for the Agent Location.

clude the use of the the visibility graph[14], the generalized Voronoi diagram (GVD)[1], trapezoidal decomposition, or probabilistic roadmaps[13]. We have developed some simple mapping procedures (similar to [7], p. 176) that construct an approximation to the GVD.

2.3 Feature Analysis

We describe here our work on 0-D features in the image, but ultimately, we hope to exploit navigation techniques to discover:

- 0-dimensional features: point or locale-centered features:
 - end points, small blob segments
 - corners
 - multi-branch points
- 1-dimensional linear features
 - straight line segments
 - curved line segments
- 2-dimensional features
 - arrowheads
 - certain symbols

An initial foray into 0-D feature extraction demonstrates the feasibility of this approach. The PRM can be used at each pixel to identify:

1. *endpoints*: the terminal part of a line segment (a dead end in terms of robot exploration)

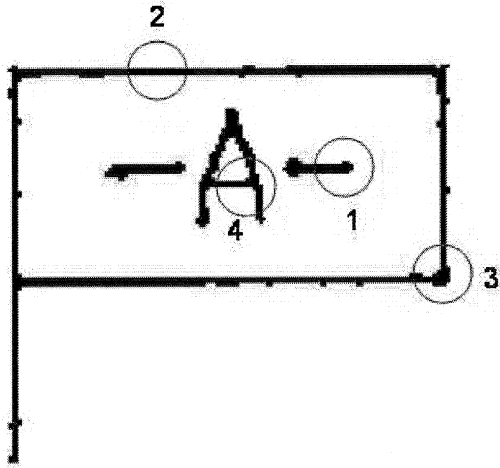


Figure 7: The four 0-D Feature Types (1: endpoint; 2: interior corridor; 3: corner; 4: multi-branch point).

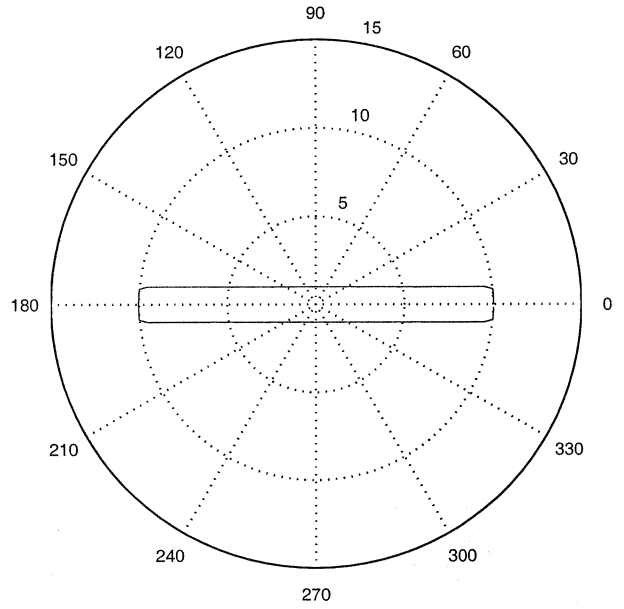


Figure 9: The Pseudo-Range Map for the Interior Corridor Feature (number 2 in Figure 7).

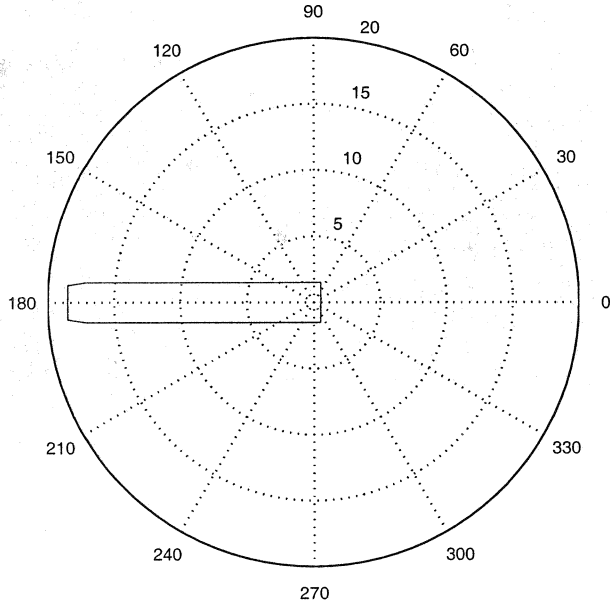


Figure 8: The Pseudo-Range Map for the Endpoint Feature (number 1 in Figure 7).

2. *interior corridor points*: two directions of travel possible, but not a corner (robot can move basically in two directions 180 degrees apart)
3. *corner points*: two directions of travel possible, but at significant angle off 180 degrees
4. *multi-branch points*: more than two directions possible for robot to explore.

Figure 7 shows examples of these four types, and Figures 8 to 11 show the PRM for each location circled in the image.

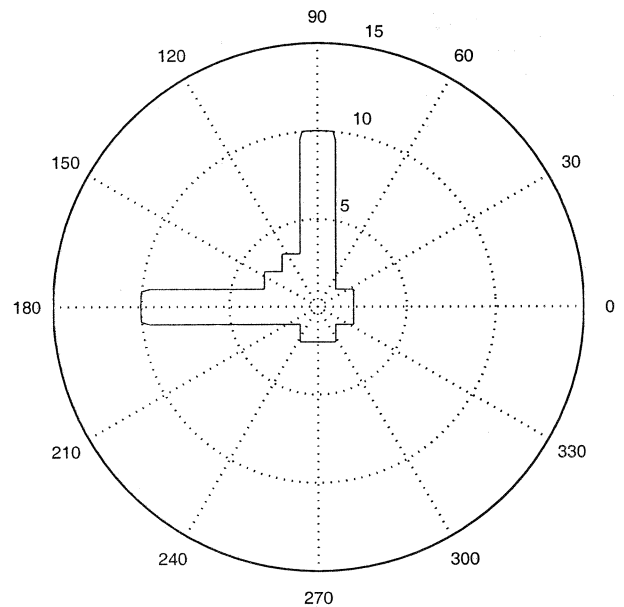


Figure 10: The Pseudo-Range Map for the Corner Feature (number 3 in Figure 7).

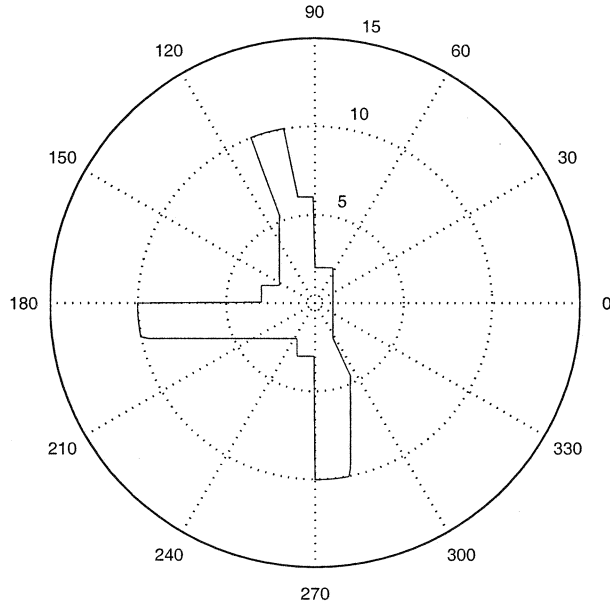


Figure 11: The Pseudo-Range Map for the Multi-Branch Feature (number 4 in Figure 7).

Given a thresholded image, this algorithm labels the 0-D features in the image; Figures 12 through 15 show the feature points extracted from the image. This is done using the polar range plots; the number of branches in the polar function tells the type of structure.

The feature classifiers work by taking into account properties of the PRM like number of peaks, maximum range, and range in the direction opposite to the maximum range (e.g., endpoint pixels have short range opposite the maximum, while corridor pixels have long range in both directions).

The performance of the proposed method, even without serious pre- and post processing, is better than that of the standard line detection algorithms.

In an attempt to determine how well our algorithm works, we explored the use of decision trees as a classification method. In particular, the information-theoretic approach described in [21] was applied, using the following attributes of the PRM:

- *attributes 1-7*: Hu invariant moments[15] of the PRM image region.
- *attribute 8*: area of the PRM image region.
- *attribute 9*: perimeter of the PRM image.
- *attribute 10*: sum of ranges in the PRM.
- *attribute 11*: total distance of the points in PRM perimeter to the point which is used to compute the PRM.

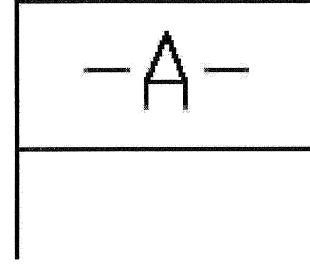


Figure 12: Endpoints Found in Image im00.

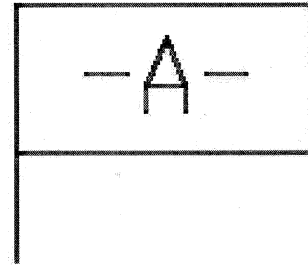


Figure 13: Corridor Points Found in Image im00.

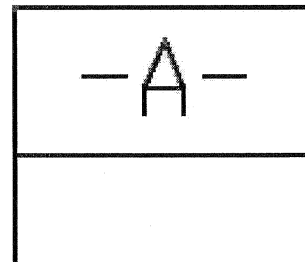


Figure 14: Corner Points found in Image im00.

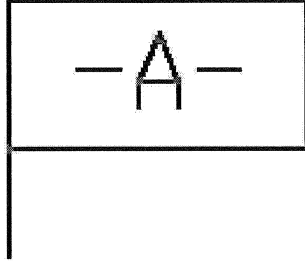


Figure 15: Branch Points Found in Image im00.

- *attribute 12*: sum of the absolute distance of the rows and cols of the PRM region point's to the row and col of the point which is used to compute the PRM, divided by the total number of points in the PRM region.
- *attribute 13*: number of branches in the PRM. (The range of the branch length must be longer than 90% of the maximum range of the PRM.)

A set of training samples were selected, and four decision trees were built: one for each 0-dimensional feature. It is interesting to note the most discriminating attribute (i.e., the first branch is determined by this attribute) for each feature: (1) endpoints: attribute 11, (2) corridors: attribute 2, (3) corners: attribute 12, and (4) branches: attribute 11. These classifiers perform well (see Section 3 on performance), but not as well as the hand written classifier.

3 Performance Evaluation

The overall system performance is evaluated in terms of the quality and computational complexity demonstrated over various image datasets. Noise is introduced during the digitization process; thus there are extraneous as well as missing objects in the resulting image. Both noise and missing data can have a large influence on the image interpretation process. In addition, blueprints might be stained, damaged during storage and usage, and scanners might have different blur, lighting, and scale factors [8]. To objectively measure how well the proposed system analyzes digitized engineering drawings, we compare results over a dataset for which we have ground truth knowledge acquired from engineering drawing datasets.

We have done the following steps for system performance evaluation:

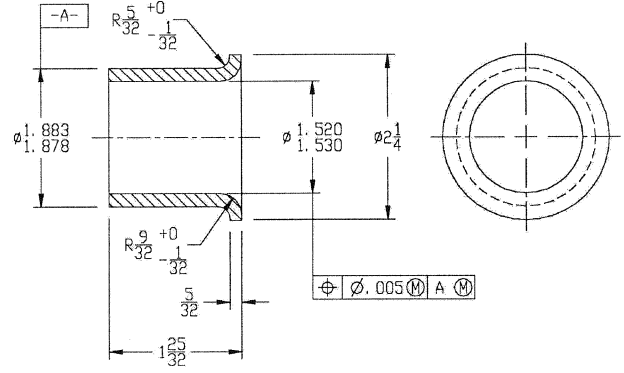


Figure 16: Test Image im00.

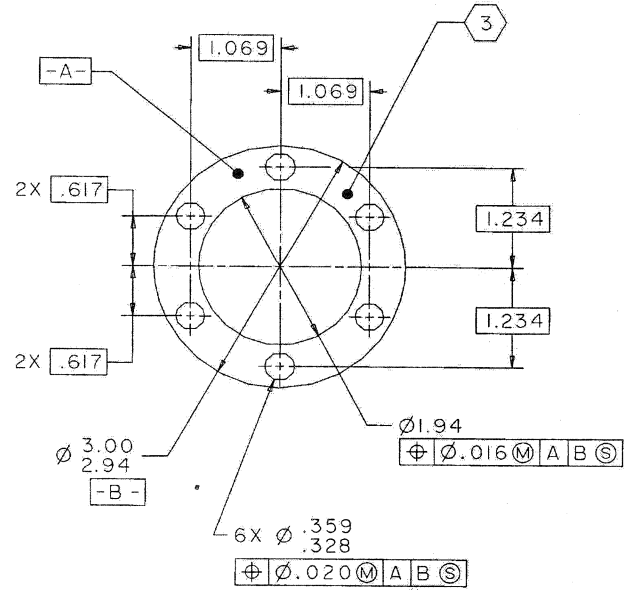


Figure 17: Test Image im17.

- Established a testbed benchmark set of five images and ground truth. These five images are shown in Figures 16 through 20.
- Run our previous feature classifier (non-PRM) on the test images. (See Table 1.)
- Run the PRM classifier on the test images. (See Table 2.)
- Developed a decision tree classifier using training data (numerical features of the PRMs). (See Table 3.)

Figures 16 through 20 show the engineering drawing test images.

To measure the performance of the algorithm, we use *recall* to mean the ratio of correct features found to total number of features, and *precision* to indicate the ratio of the number of correct feature responses to the total number of feature responses. Tables 1

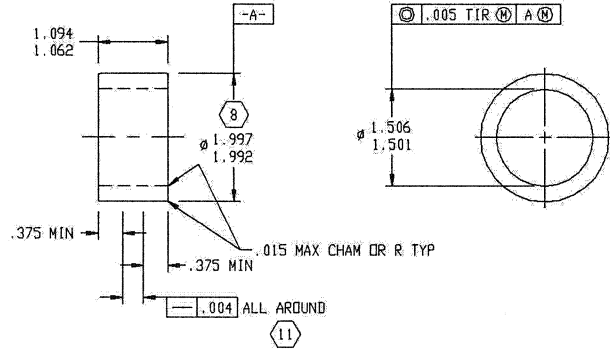


Figure 18: Test Image im18.

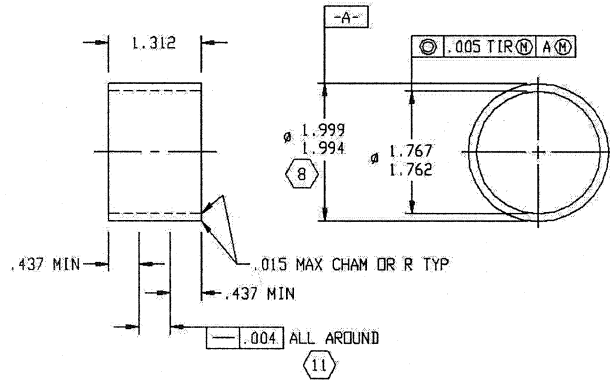


Figure 19: Test Image im19.

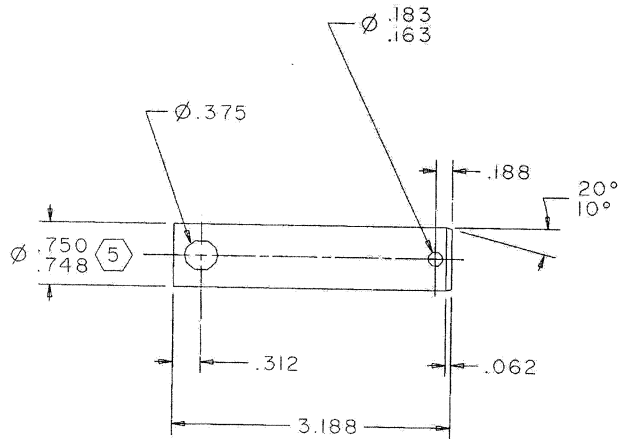


Figure 20: Test Image im22.

through 3 show the *recall* results from these experiments, while Tables 4 through 6 give the *precision* results.

Image	F_end	F_corr	F_corn	F_bra
im00	90.45	99.55	72.60	81.22
im17	92.41	99.25	65.11	89.25
im18	96.38	98.64	73.27	71.90
im19	95.59	98.95	73.88	86.36
im22	84.85	99.92	36.72	86.75

Table 1. Recall Percentage Correct for Non-PRM Method.

Image	F_end	F_corr	F_corn	F_bra
im00	100.0	98.70	100.0	100.0
im17	96.97	98.84	100.0	100.0
im18	100.0	99.07	99.63	100.0
im19	98.64	98.95	100.0	95.87
im22	97.32	98.09	100.0	98.92

Table 2. Recall Percentage Correct for PRM Method.

Image	F_endpt	F_corr	F_corn	F_bra
im00	100.0	87.61	85.48	99.53
im17	97.32	82.61	68.85	100.0
im18	99.55	84.91	84.49	80.99
im19	100.0	84.91	81.34	90.91
im22	97.73	91.85	46.88	97.59

Table 3. Recall Percentage Correct for Decision Tree Method.

Image	F_end	F_corr	F_corn	F_bra
im00	43.36	100.0	42.87	43.25
im17	35.10	100.0	28.64	41.52
im18	60.96	100.0	51.66	35.01
im19	53.94	100.0	63.23	34.92
im22	34.73	100.0	29.20	45.93

Table 4. Precision Percentage Correct for Non-PRM Method.

Image	F_end	F_corr	F_corn	F_bra
im00	35.82	100.0	42.59	50.11
im17	55.39	100.0	38.31	39.45
im18	69.89	100.0	47.83	57.56
im19	68.55	100.0	48.57	58.27
im22	31.06	100.0	28.20	44.50

Table 5. Precision Percentage Correct for PRM Method.

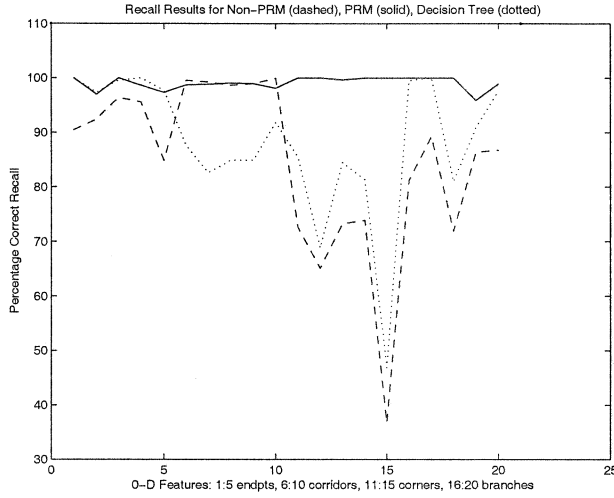


Figure 21: Percentage Correct Recall.

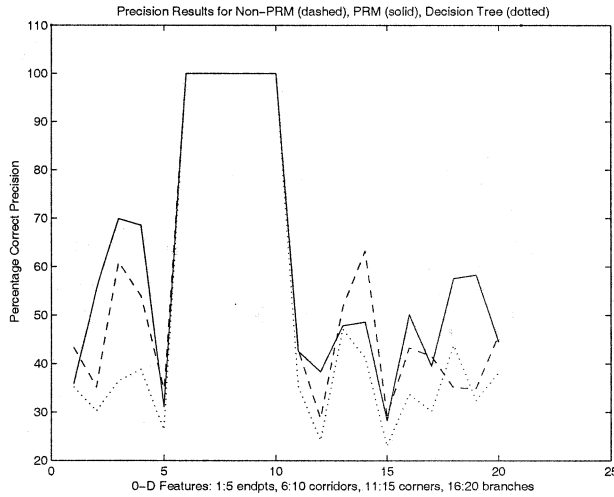


Figure 22: Percentage Correct Precision.

Image	F_endpt	F_corr	F_corn	F_bra
<i>im00</i>	35.17	100.0	35.35	33.71
<i>im17</i>	30.17	100.0	24.15	30.14
<i>im18</i>	36.42	100.0	47.14	43.79
<i>im19</i>	38.79	100.0	41.21	32.43
<i>im22</i>	26.35	100.0	22.96	38.18

Table 6. Precision Percentage Correct for Decision Tree Method.

As can be seen from the performance data in Figures 21 and 22, the static PRM feature classification method works very well with regard to recall, but requires a post-processing step to ensure good precision.

4 Conclusions and Future Work

We have demonstrated that the use of static Pseudo Range Maps yields high percentage detection of point features in engineering drawing images. We

are currently investigating:

- *Agent motion during feature recognition.* First, 0-dimensional features will be analyzed, then 1-dimensional, and finally, 2-dimensional.
- *Learning characteristics of the line drawing data.* Let the trajectory of an agent as it explores a drawing be considered an element. Then one approach to finding related parts of the drawing, or parts that are similar to a known model, is to use the affinity graph method[6] to cluster the elements into similar classes.

We are currently pursuing these two lines of development. In addition, we intend to expand the domain of application to other datasets, including: map features, handwritten and other documents.

Acknowledgments

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References

- [1] F. Aurenhammer. Voronoi Diagrams – A Survey of a Fundamental Geometric Structure. *ACM Computing Surveys*, 23:345–405, 1991.
- [2] G. Dissanayake, P. Newman, S. Clark, H.F. Durrant-Whyte, and M. Csorba. A Solution to the Simultaneous Localisation and Map Building (SLAM) Problem. *IEEE-T Robotics and Automation*, 17(3):229–241, June 2001.
- [3] Dov Dori. Dimensioning Analysis toward automatic understanding of engineering drawings. *Communications of the ACM*, 35(10):92–103, October 1992.
- [4] D.S.Guru, B.H.Shekar and P.Nagabhushan. A simple and robust line detection algorithm based on eigenvalue analysis. *Pattern Recognition Letters*, 25(1):1–13, 2004.
- [5] Feng Su, Jiqiang Song, Chiew-Lan Tai and Shijie Cai. Dimension Recognition and Geometry Reconstruction in Vectorization of Engineering Drawings. In *Computer Vision and Pattern Recognition, 2001 (CVPR 2001)*, volume 1, pages 682–688, 2001.
- [6] D.A. Forsyth and J. Ponce. *Computer Vision: A Modern Approach*. Prentice Hall, Upper Saddle River, NJ, 2003.
- [7] H. Choset and K. Lynch and S. Hutchinson and G. Kantor and W. Burgard and L. Kavraki and S. Thrun. *Principles of Robot Motion*. MIT Press, Cambridge, MA, 2005.

- [8] Thomas C. Henderson. Explicit and Persistent Knowledge in Engineering Drawing Analysis. Research Report UUCS-03-018, School of Computing, University of Utah, Salt Lake City, Utah, 2003.
- [9] Thomas C. Henderson and Lavanya Swaminathan. Form Analysis with the Nondeterministic Agent System (NDAS). In *Proceedings of 2003 Symposium on Document Image Understanding Technology*, pages 253–258, Greenbelt, VA, April 2003.
- [10] Thomas C. Henderson and Lavanya Swaminathan. NDAS: The Nondeterministic Agent System for Engineering Drawing Analysis. In *Proceedings of International Conference on Integration of Knowledge Intensive Multi-agent System*, pages 512–516, October 2003.
- [11] Thomas C. Henderson and Lavanya Swaminathan. Symbolic Pruning in a Structural Approach to Engineering Drawing Analysis. In *Proceedings of International Conference on Document Analysis and Recognition*, pages 180–184, August 2003.
- [12] Jiqiang Song, Min Cai, Michael R. Lyu and Shijie Cai. A New Approach for Line Recognition in Large-size Images Using Hough Transform. In *International conference on pattern recognition (ICPR'02)*, volume 1, page 10033, 2002.
- [13] L.E. Kavvaki, P. Svestka, J.C. Latombe, and M.H. Overmars. Probabilistic Roadmaps for Path Planning in High-Dimensional Configuration Spaces. *IEEE-T Robotics and Automation*, 12(4):566–580, June 1996.
- [14] J.C. Latombe. *Robot Motion Planning*. Kluwer Academic Publishers, Boston, MA, 1991.
- [15] Martin Levine. *Vision in Man and Machine*. McGraw-Hill Book Company, New York, 1985.
- [16] M.Mattavelli, V.Noel, and E.Amaldi. A New Approach for Fast Line Detection Based on Combinatorial Optimization. In *10th International Conference on Image Analysis and Processing*, volume 1, page 168, 1999.
- [17] M. Montemerlo and S. Thrun. Real Time Data Association for FastSLAM. In *Proceedings of International Conference on Robotics and Automation*, Taipei, Taiwan, 2003.
- [18] Robert M. Haralick and Linda G. Shapiro. *Computer and Robot Vision*. Addison-Wesley, Reading, MA, 1992.
- [19] S. H. Joseph, T. P. Pridmore, and M. E. Dunn. *Toward the automatic interpretation of mechanical engineering drawings*. Computer Vision and Image Processing(A. Bartlett, Ed.), New York: Kogan Page, 1989.
- [20] Jiqiang Song, Michael R. Lyu, and Shijie Cai. Effective Multiresolution Arc Segmentation: Algorithms and Performance Evaluation. *IEEE-T Pattern Analysis and Machine Intelligence*, 26(11):1491–1506, November 2004.
- [21] Stuart Russell and Peter Norvig. *Artificial Intelligence*. Prentice Hall, Upper Saddle River, New Jersey, 2003.
- [22] Lavanya Swaminathan. Agent-Based Engineering Drawing Analysis. Master's thesis, University of Utah, Salt Lake City, Utah, May 2003.
- [23] K. Tombre and D. Antoine. Analysis of Technical Documents using A Priori Knowledge. In *IAPR Workshop Syntactic and Structural Pattern Recognition, Pont--Mousson, France*, pages 178–189, 1988.
- [24] K. Tombre and Dov Dori. Interpretation of engineering drawings. In *Handbook of Character Recognition and Document Image Analysis*, pages 457–484, 1997.
- [25] Y.Yu, A.Samal, and S.C.Seth. A System for Recognizing a Large Class of Engineering Drawings. *IEEE Transactions on PAMI*, 19(8):868–890, 1997.