Multistrategy Learning for Computer Vision

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by

Bir Bhanu
Principal Investigator

University of California
College of Engineering
Riverside, CA 92521-0425

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6. AUTHOR(S)
Professor Bir Bhanu

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
University of California
College of Engineering
Riverside CA 92521-0425

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Current IU algorithms and systems lack the robustness to successfully process imagery acquired under real-world scenario. They do not provide the necessary consistency, reliability and predictability of results. Robust 3-D object recognition, in practical applications, remains one of the important but elusive goals of IU research. With the goal of achieving robustness, our research at UCR is directed towards learning parameters, feedback, contexts, features, concepts, and strategies of IU algorithms for model-based object recognition. Our multistrategy learning-based approach is to selectively apply machine learning techniques at multiple levels to achieve robust recognition performance. At each level, appropriate evaluation criteria are employed to monitor the performance and self-improvement of the system. The results of our research are being applied in automatic target recognition, autonomous navigation, and image and video databases.

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FINAL REPORT
MULTISTRATEGY LEARNING FOR COMPUTER VISION
GRANT NUMBER F49620-95-1-0424

PI: Bir Bhanu

UC Riverside

1. SUMMARY

This final report describes the work that has been performed under the DARPA/AFOSR grant F49620-95-1-0424 on "Multistrategy Learning for Computer Vision," during the period from July 1, 1995 to June 30, 1998. In the following we present a summary of objectives and accomplishments achieved during the course of the program. Selected papers published during the course of the program are attached with this report.

2. OBJECTIVES

Current IU algorithms and systems lack the robustness to successfully process imagery acquired under most real-world scenarios. They do not provide the necessary consistency, reliability and predictability of results. Robust 3-D object recognition remains one of the important but elusive goals of IU research for practical applications. With this goal of achieving robustness, our research at the University of California at Riverside (UCR) is directed towards learning parameters, feedback, contexts, features, concepts, and strategies of IU algorithms for model-based object recognition.

Our multistrategy learning-based IU approach selectively applies machine learning techniques in innovative ways at multiple levels to achieve robust recognition performance. At each level, appropriate evaluation criteria are employed to monitor the performance and self-improvement of the system.

The results of our research are being applied in automatic target recognition, autonomous navigation, and image and video databases.

3. MAJOR ACCOMPLISHMENTS/NEW FINDINGS

A. CLOSED-LOOP IMAGE UNDERSTANDING SYSTEMS (Documents #2, 3 & 7)

Robustness of an IU system can be enhanced using feedback. However, how to control feedback in a multi-level IU system has been a long-standing problem in the field of computer vision and pattern recognition. We have developed reinforcement learning-based techniques that show promise in approaching this problem [please see attached documents 2 and 3].

Our theoretically sound approaches to control feedback use the results of recognition to learn segmentation and feature extraction parameters for robust model-based recognition. They are based on the use the team of learning automata algorithm and the delayed reinforcement learning algorithm.

The closed-loop object recognition system evaluates the performance of segmentation and feature extraction by using the recognition algorithm as part of the evaluation function. Recognition confidence is used as a reinforcement signal to the image segmentation or feature extraction processes. By using the recognition algorithm as part of the evaluation function, the system is able to develop recognition strategies automatically, and to recognize objects accurately in newly acquired images. As compared to the genetic algorithm based techniques that we have developed earlier which simply search a set of parameters that optimize a prespecified evaluation function, here we have a recognition algorithm as part of the evaluation function.

Using the Phoenix algorithm for the segmentation of color images, a clustering-based algorithm for the recognition of occluded 2-D objects and a team of learning automata algorithm, or a delayed reinforcement learning algorithm, we show that in simple real scenes with varying environmental conditions and camera motion, effective low-level image analysis and feature extraction can be performed. We show the performance improvement of an IU system combined with learning over an IU system with no learning.

The results of this research are being used for model-based recognition of targets in SAR images acquired under extended operating conditions (please see "Adaptive Target Recognition Using Reinforcement Learning," by Bhanu, Lin, Jones, and Peng (DARPA IUW98)). They have also been applied to the problem of autonomous navigation (please see attached document #7).

B. LEARNING BASED INTEGRATED RECOGNITION AND SEGMENTATION (Document #4)

We have developed a general approach to image segmentation and object recognition that can adapt to the changing environmental conditions. It allows the automated acquisition of recognition strategies in dynamic environments. The learning paradigm used here is reinforcement learning, same as in **A.** above. Incorporation of domain knowledge into a reinforcement learning paradigm and its efficient implementation are important challenges posed by computer vision applications. We have used the edge-border coincidence for both local and global segmentation evaluation. However, since this measure is not reliable for object recognition, it is used in conjunction with model matching in a closed-loop object recognition system. Segmentation parameters are learned using a reinforcement learning algorithm that is based on a team of learning automata and uses edge-border coincidence or the results of model matching as reinforcement signals. The performance improvements are shown in the attached document #4.

C. SCALABILITY OF GENETIC LEARNING FOR ADAPTIVE SEGMENTATION (Document #8)

The problem is to learn algorithm parameters, develop algorithms and evaluation criteria for multisensor image segmentation and recognition from images acquired under varying environmental conditions. We have developed techniques based on genetic learning and other hybrid methods such as a combination of genetic algorithms and hill climbing.

Our initial research using outdoor video imagery and the Phoenix algorithm has demonstrated that (a) adaptive image segmentation can provide over 30% improvement in performance, as measured by the quality of segmentation, over non-adaptive techniques, and (b) learning from experience can be used to improve the performance over time. In our current work, we show that our approach scales with respect to the number of parameters and the size of the search space. Genetic learning combined with a hill-climbing technique is able to adaptively select good segmentation parameters and to generate the best result using the least number of segmentations. In experiments designed to evaluate the scalability of our approach we find that for the case of a four Phoenix parameter set we only search about 0.5% of the (1 million size) search space.

D. LEARNING TO INTEGRATE CONTEXT WITH CLUTTER MODELS (Document #10)

The problem is to integrate contextual information with clutter models for target detection and recognition. Current image metrics commonly used to characterize images do not correlate well with the performance of target recognition systems.

The contextual parameters, which describe the environmental conditions for each training example, are used in a reinforcement learning paradigm to improve the clutter models and enhance target detection performance under multi-scenario situations. New Gabor transform-based features and other statistical image features are used to capture the statistical properties of natural backgrounds in visible and FLIR images. The non-incremental self-organizing map approach commonly used in an unsupervised mode is extended, by the addition of a near-miss injection algorithm, and used as an incremental supervised learning process for clutter characterization.

A fast algorithm to compute the Gabor transform of a given image has been implemented. We have implemented two new Gabor transform-based feature groups and tested their classification performance on natural backgrounds. Experimental results show that the two feature groups could capture certain characteristics of the backgrounds, which are consistent with our theoretical expectations based on the physical meaning of each attribute within the feature group. Using second generation FLIR images, four contextual parameters (time of the day, depression angle, range to the target and air temperature) and 5 feature groups, we find 100% detection rate, 10% false alarm rate and significant improvement in the confidence for classifying a feature cell (rectangular regions in an image) as a clutter or a target.

E. INPUT ADAPTATION USING MODIFIED HEBBIAN LEARNING (Document #9)

The problem is to improve the performance of an IU algorithm by adapting its input data to the desired form so that it is optimal for the given algorithm.

The two general methodologies for the performance improvement of an IU system are based on optimization of algorithm parameters and adaptation of the input. Unlike the genetic learning case for adaptive image segmentation, here we focus on the second methodology and use modified Hebbian learning rules to build adaptive feature extractors which transform the input data into the desired form for a given algorithm. Learning rules are based on different loss functions and are suitable for extracting expressive or discriminating features from the input.

The feasibility of the approach is shown by designing an input adaptor for a thresholding algorithm for target detection using SAR and FLIR images. The results are excellent with the input adaptor, compared to the case with no input adaptor.

F. SYSTEM FOR AIRCRAFT RECOGNITION (Documents #6 & 5)

We developed an IU system for aircraft recognition. The complete report on the system with its capabilities and limitations are described in document #6. Document #5 describes a multistrategy learning based system for aircraft recognition. We also investigated the development of a case-based reasoning approach for learning strategies for model-based recognition.

G. COMPREHENSIVE PAPER (Document #1)

Wrote and refined a comprehensive paper on applying learning techniques to computer vision problems.

3. PERSONNEL SUPPORTED

Xin Bao, Ming Li, Yajie Yang, Jing Peng, Jianing Feng, Y. Lin and Bir Bhanu

4. PUBLICATIONS

(a) Published:

- J. Ming and B. Bhanu, "Oracle: An Integrated Learning Approach for Object Recognition," *Int. Journal of Pattern Recognition and Artificial Intelligence*, Vol. 11, No. 6, pp. 961-990, September 1997.

- B. Bhanu, X. Wu, and S. Lee, "Genetic Algorithms for Adaptive Image Segmentation," Chapter 11 in "Early Visual Learning," edited by S. Nayar and T. Poggio, Oxford University Press, pp. 269-298, 1996.

- J. Peng and B. Bhanu, "Reinforcement Learning for Adaptive Image Segmentation and Feature Extraction," *IEEE Trans. on Systems, Man and Cybernetics*, Vol. 28, No. 3, pp. 482-488, 1998.

- J. Peng and B. Bhanu, "Closed Loop Object Recognition Using Reinforcement Learning," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 20, No. 2, pp. 139-154, 1998.

- B. Bhanu, "Image Understanding Research at UC Riverside: Integrated Recognition, Learning and Image Databases," *Proc. DARPA Image Understanding Workshop*, New Orleans, LA, pp. 483- 494, May 13-15, 1997.

- B. Bhanu, X. Bao and J. Peng, "Self-Optimizing Integrated Image Segmentation and Object Recognition," *Proc. DARPA Image Understanding Workshop*, New Orleans, LA, pp. 1145-1154, May 13- 15, 1997.

- B. Bhanu and Bing Tian, "Multiple Stochastic Models for Recognition of Objects in SAR Images," *Proc. DARPA Image Understanding Workshop*, New Orleans, LA, May 13-15, 1997.

- S. Rong and B. Bhanu, "Modeling Clutter and Context for Target Detection in Infrared Images," *IEEE Conference on Computer Vision and Pattern Recognition*, San Francisco, CA, pp. 106-113, June 16-20, 1996.

- J. Peng and B. Bhanu, "Closed-Loop Object Recognition Using Reinforcement Learning," *IEEE Conference on Computer Vision and Pattern Recognition*, San Francisco, CA, pp. 538-543, June 16-20, 1996.

- Y. Zheng and B. Bhanu, "Adaptive Object Detection From Multisensor Data," *IEEE International Conference on Multisensor Fusion and Integration of Intelligent Systems,* Washington, D.C., pp. 633-640, December 8-11, 1996.

- J. Peng and B. Bhanu, "Delayed Reinforcement Learning for Closed-Loop Object Recognition," *Proc. International Conference on Pattern Recognition,* Vienna, Austria, pp. 310-314, August 26-29, 1996.

- B. Bhanu, S. Lee and J. Ming, "Adaptive Image Segmentation Using a Genetic Algorithm," *IEEE Transactions on Systems, Man and Cybernetics,* Vol. 25, No. 12, pp. 1543-1567, December 1995.

- B. Bhanu, S. Lee and S. Das, "Adaptive Image Segmentation Using Genetic and Hybrid Search Methods," *IEEE Transactions on Aerospace and Electronic Systems,* Vol. 31, No. 4, pp. 1268-1291, October 1995.

- B. Bhanu and J. Peng, Adaptive Integrated Image Segmentation and Object Recognition," *Eleventh Vision Interface Conference,* Vancouver, Canada, pp. 471-478, June 18-20, 1998.

- J. Peng and B. Bhanu, "Learning to Perceive for Autonomous Navigation in Outdoor Environments," *IEEE Workshop on Perception for Mobile Agents,* Santa Barbara, CA, pp. 95-104, June 1998.

- S. Das and B. Bhanu, "A System for Model-Based Object Recognition in Perspective Aerial Images," *Pattern Recognition,* Vol. 31, No. 4, pp. 465-491, 1998.

(c) Submitted but not yet accepted:

- B. Bhanu, X. Bao and J. Peng, "Adaptive Integrated Image Segmentation and Object Recognition," submitted to *IEEE Trans. on Image Processing,* revised May 1998.

- S. Das and B. Bhanu, "Computational Vision: A Learning Perspective," submitted to *ACM Computing Surveys,* (under revision).

- J. Peng and B. Bhanu, "Learning to Perceive Objects for Autonomous Navigation," submitted to *Autonomous Robots,* 1998.

5. ACKNOWLEDGMENTS

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