Closed-Loop Adaptive Image Segmentation

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Abstract

One of the fundamental weaknesses of current computer vision systems used in outdoor applications is their inability to adapt the segmentation process as real-world changes occur in the image. We present a closed loop image segmentation system that incorporates a genetic algorithm to adapt the segmentation process to changes in image characteristics caused by variable environmental conditions. The genetic algorithm efficiently searches the hyperspace of segmentation parameter combinations to determine the parameter set which maximizes the segmentation quality criteria. We present a summary of the experimental results that demonstrates the ability to perform adaptive image segmentation and to learn from experience using a collection of outdoor color imagery.

1. Introduction

Image segmentation is typically the first, and most difficult task of any automated computer vision process. All subsequent tasks including object detection, feature extraction, and object recognition rely heavily on the quality of the segmentation process. Despite the large number of segmentation techniques presently available, no general methods have been found that perform adequately across a diverse set of imagery.

The key to effective image segmentation is the selection of the appropriate segmentation algorithm control parameters for each image. However, this is very difficult because 1) the number of control parameters is typically quite large, 2) the control parameters interact in complex ways and cannot be mathematically modeled, 3) image variation causes the computation of segmentation quality to change for every image, and 4) the definition of segmentation quality is very complex. Selection of control parameters can be viewed as a search through the space of all possible parameter combinations in order to locate the parameter set which yields the highest segmentation quality.

Genetic algorithms [2,3], which are designed to efficiently locate an approximate global maximum in a search space, show great promise in solving the parameter selection process encountered in image segmentation. Since they use simple recombinations of existing high quality parameter sets and a method of measuring current segmentation quality, they do not require complex segmentation quality surface descriptions, domain specific knowledge, or measures of goal distance. They are also independent of the particular image segmentation technique that is used.

2. Adaptive Image Segmentation System

The block diagram of our adaptive image segmentation system is shown in Figure 1. After acquiring an input image, the system analyzes the image characteristics (first order statistics and histogram properties; 48 total image properties from R,G,B, and Y components) and passes this information, in conjunction with the external variables, to the genetic learning system.

Using the image characteristics, the genetic learning system selects a set of possible segmentation control parameters by comparing the current image properties with those of images processed previously (stored in the global population). These parameter sets form the seed population for the genetic process. This population is maintained and updated by the genetic learning system.

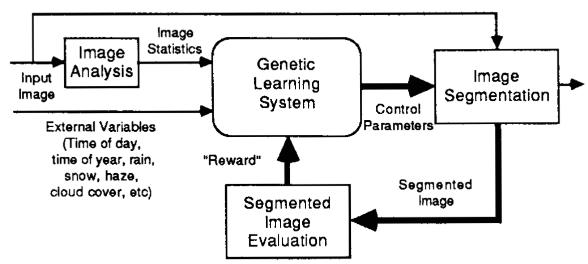

Figure 1: Adaptive Image Segmentation System.

Each of the parameter sets is passed to the image segmentation algorithm where the image is segmented. The Phoenix segmentation algorithm has been used in this work. The segmentation results are then evaluated using a collection of five separate segmentation quality measures. These evaluation criteria measure the local (object specific) as well as global (overall image) segmentation quality of the image. The results of all five measures are combined and normalized in a weighted sum value that represents overall segmentation quality.

The evaluation results are fed back into the genetic learning system as a "reward" to the associated parameter set. If none of the members in the seed population is acceptable, the genetic learning system begin recombining the parameter sets using the crossover and mutation genetic operators. This cycle repeats until acceptable segmentation quality results have been achieved.

3. Experimental Results

A database of 20 outdoor images was collected to demonstrate the system's ability to adapt to real world conditions. The images were collected using a stationary camera and were acquired every 15 minutes over a 5 hour period. The weather and position of the sun varied during this time, creating significant diversity in the characteristics of the images in the sequence.

For these experiments, the size of the global population was set at 100 individuals, the local or seed population was set at 10 members, the crossover rate was 0.8, and the mutation rate was 0.01. Two control parameters (maxmin and hsmooth) were selected to control the behavior of the Phoenix segmentation algorithm.

The images were separated into two groups of ten images (odd and even numbered frames) in order to obtain imagery for training and testing purposes. Each training image was processed by the adaptive segmentation system using no a priori knowledge (i.e., seed populations are randomly created). Once all training images had been processed, the populations from each of these images were combined to create the global population used during testing. The testing experiments utilize the information stored in the global population to improve the selection of initial parameter sets and improve the quality of the segmentation results.

Figure 2 summarizes the results of the tests preformed on the outdoor imagery. The adaptive image segmentation technique is contrasted with performance obtained using more common techniques for image segmentation. The *default parameter* results are achieved using the suggested parameter settings built into the Phoenix algorithm.

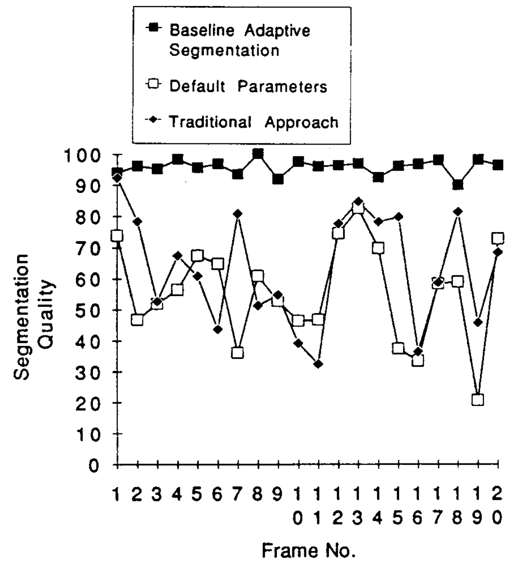

Figure 2: Comparison of the adaptive image segmentation system with other commonly used techniques.

The *traditional approach* allows the user to manually optimize the segmentation quality using the first image and uses these settings for the remainder of the image database. As the figure shows, the performance of the adaptive segmentation system is much better (higher quality and stable behavior) than the alternative approaches.

Further experiments were carried out using this collection of imagery including the simulation of a multi-day image sequence and a comparison of the adaptive technique with purely random search. Complete details of these experiments are presented by Bhanu et. al. [1].

4. References

[1] B. Bhanu, S. Lee, J. Ming, "Self-Optimizing Control System for Adaptive Image Segmentation, *Proceedings of DARPA Image Understanding Workshop*, pp. 583-596, 1990.

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