

AUTOMATIC ADAPTATION OF IMAGE SEGMENTATION CONTROL PARAMETERS FOR OUTDOOR SCENES

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Abstract

This paper proposes a method for automatic adaptation of segmentation control parameters based on Genetic Algorithms. The goals of automatic adaptation of segmentation parameters in this research are to provide continuous adaptation to normal environmental variation conditions such as (time of day, weather) to exhibit learning capability and to provide robust performance when interacting with a dynamic environment. The research intended to adapt the performance of a well known existing segmentation method (Recursive region growing Algorithms) across a wide variety of environmental conditions which cause changes in the image characteristics and maximizes the segmentation quality measures. Experimental results are given that indicate the ability to adapt the segmentation performance in outdoor color image with high quality segmentation result in a minimal number of generations.

التكيف التلقائي لعوامل سيطرة تجزئة الصورة للمناظر الخارجية

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الخلاصة

في هذه الورقة نقترح طريقة تعتمد على الخوارزمية الجينية للتكيف التلقائي لعوامل السيطرة في تقسيم الصورة. في هذا البحث اهداف التكيف التلقائي لعوامل التقسيم هو توفير التكيف الديناميكي مع التغيرات في الظروف البيئية والطبيعية مثل (الوقت في اليوم, حالة الطقس) لاطهار قابلية التعلم ولتقديم الاداء القوي عندما تتفاعل مع بيئة ديناميكية. البحث موجه نحو تكييف أداء طريقة تقسيم الصور المعروفة (خوارزمية نمو المنطقة المتكرر) عبر مجموعة واسعة من الظروف البيئية التي تسبب تغيرات في خصائص الصورة ويزيد من مقاييس الجودة العالية للصورة المقسمة. نتائج التجارب العملية تشير الى القدرة على تكيف اداء التقسيم في الصور الملونة الخارجية مع نتائج جودة عالية باقل عدد من الاجيال.

1-Introduction

Image segmentation is a fundamental process in many image, video, and computer vision applications. It is often used to partition an image into meaningful separate regions, which ideally correspond to different real-world

objects. It is a critical step towards content analysis and image understanding [1].

Currently, there are a large number of segmentation techniques that are available. However, these techniques rarely demonstrate the robustness required for practical applications of image understanding. The difficulty arises

since the segmentation performance needs to be adapted to the changes in image quality. Image quality is affected by variations in environmental conditions, imaging devices, time of day, etc. Thus, one of the fundamental weaknesses of current image segmentation algorithms is their inability to adapt the segmentation process as real-world changes occur in the image. Only after many modifications to an algorithm's control parameter can any current image segmentation technique be used to handle the diversity of image encountered in real-world applications. While there are threshold selection techniques which adapt to local image properties in a single image for image segmentation, these techniques do not adapt local thresholds from frame to frame so as to compensate for changes in images caused by variations in environmental conditions.

The performance of any segmentation technique depends on the segmentation quality, and that depends on two major factors: the selected segmentation algorithm and the segmentation parameter settings. Any technique will eventually yield poor performance if it does not adapt to the environmental variations. Therefore, in this paper we attempt to address this fundamental limitation in developing useful computer vision systems for practical scenario by developing a system which automatically adjusts the performance of segmentation algorithm. The system is based on changing the control parameters of the segmentation algorithm such that it will be operational across a wide diversity of image characteristics and application scenario [2].

2-Genetic Algorithm's Principle

Genetic Algorithms (GA's) are non-deterministic stochastic search/optimization methods that utilize the theories of evolution and natural selection to solve a problem within a complex solution space. They are computer-based problem solving systems which use computational models of some of the known mechanisms in evolution as key elements in their design and implementation. They are based on the principle of the Darwin's Theory of Evolution in that individual characteristics are transmitted from parents to children over generations, and individuals more adapted to the environment have greater chances to survive and pass on particular characteristics to their offspring[3].

2-1 Genetic Algorithm's Structure

GA's work with a *population* of "*individuals*", each representing a possible solution to a given problem, and their relevant characteristics with respect to the problem are called *genes*.

Each individual in a particular *generation* is assigned a "*fitness function*" according to how good a solution to the problem it is. GAs proposes an evolutionary process to search for solutions that maximize or minimize a fitness function. This search is made iteratively, over generations of individuals. The highly-fit individuals are given opportunities to "*reproduce*", with other individuals in the population. This produces new individuals as "*offspring*", which share some features taken from each "*parent*". The least fit members of the population are less likely to get selected for reproduction, and so "*die out*".

The creation of the new individuals is done by the use of *genetic operators* [4].

2-2 Genetic Algorithm Operators

The *crossover* and *mutation* are the most important part of the genetic algorithm. The performance of the algorithm is mainly influenced by these two operators. Crossover operators act by mixing genes between two individuals to create a new one that inherits characteristics of their parents. The general idea is that as an individual's fitness is a function of its characteristics, the exchange of good genes can produce better fitted individuals, depending on the genes inherited from their parents. Mutation is applied to each child individually after crossover. It randomly alters each gene values respecting the genes' search space. Mutation is important to introduce a random component in the solution's search, in order to avoid convergence to local minima [4].

3-Segmentation Algorithm and Control Parameters

The segmentation procedure used in this work is based on region growing algorithm. The algorithm is a stepwise local optimization procedure that minimizes the average heterogeneity of the image objects.

Objects grow from single pixels, merging to neighboring pixels. In each processing step, an object can be merged to the neighbor that provides for the smallest growth of global heterogeneity. The merging decision is based on

minimizing the resulting object's *weighted heterogeneity*, an arbitrary measure of heterogeneity weighted by object size. The heterogeneity measure has a spectral and a spatial components. Spectral heterogeneity is defined over the spectral values of the pixels belonging to the object, and it is proportional to the standard deviation of the pixels' spectral values, weighted by arbitrary spectral band weights [2].

The spatial heterogeneity component is based on the deviation of the object's shape from a compact and a smooth shape. Compactness is defined as the ratio of the perimeter of the object and the square root of its area (the number of pixels it contains), and smoothness is defined as the ratio of the object's perimeter and the length of its bounding box (parallel to the image borders). To simulate the parallel growth of the segments, objects are selected for merging only once in each iteration, in an evenly distributed fashion.

The merging decision mechanism is of key importance to this work, as it is where the external parameters of the segmentation procedure are employed. A *fusion factor* is calculated for each neighbor of the selected object, the neighbor for which this factor is minimum will be merged to the object, but only if the fusion factor is smaller than a certain threshold, defined as the square of the so called *scale parameter*. The procedure stops when no more objects can be merged [2].

4-The Framework of The Proposed Adaptive System

The goal of this research is to develop and demonstrate an adaptive image segmentation technique for dynamic outdoor imagery. The segmentation algorithm is integrated with genetic learning algorithm to be able to adapt to the changes in image characteristics caused by variable environmental conditions, such as time of day, weather (cloud, sunny, rain, etc.).

A simplified block diagram of adaptive image segmentation system is shown in Figure (1)

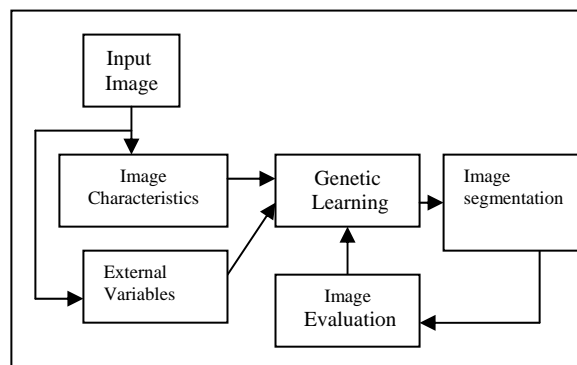


Figure 1 : Block Diagram of Adaptive Image Segmentation System

4-1 Input Image Characteristics

The color input image is analyzed so that a set of features is extracted to aid in the selection of parameter process.

A set of image characteristics is obtained which measure various image properties of the digital image itself as well as by observing the environment conditions in which the image is acquired. Each type of information encapsulates knowledge that is used to determine a set of appropriate starting points for the parameter adaptation process.

The (9) statistics features used are[5,6]:-

mean, variance, skewness, energy, entropy, kurtosis, maximum peak heigh, maximum peak location, maximum peak-to-valley ratio.

External variables are also used to characterize an input image. These factors specify the conditions under which the image is acquired. They include information such as time of day, and weather condition (cloud, sunny, temperature, humidity, snow, rain). All these conditions affect the quality of the image, which, in turn, necessitates changes in control parameters.

For the experiments in this paper, we compute (9) properties for each color component (Red, Green, and Blue) of the image and these yield a list of (27) elements. In addition, two external variables, time of day and weather condition are utilized in the outdoor experiments to characterize each image. The external variables are represented symbolically in the list structure (e.g., *time*=10am,7am,etc, and *weather conditions*=sunny, cloudy, etc.). The two external variables are added to the list to create an image characteristics list of (29) elements for the outdoor experiments.

The outdoor image database consists of 10 frames, each frame is digitized at 480 by 480.

The images are collected **approximately** every 25 minutes over a four hour period using color video camera. This type of image data simulates a photo scenario in which the camera position is fixed and the image undergoes significant change over time. Varying light levels is the most prominent change throughout the image sequence, although the environmental conditions also created varying object highlights, moving shadows, and many subtle contrast changes between the objects in the image.

4-2 Genetic Learning System

After the image statistics and external variables are obtained, an initial population is created for the genetic adaptive component. A knowledge-based system is used to represent the image characteristics and associated segmentation parameters shown in figure (2a) and represented in binary string with genetic algorithm.

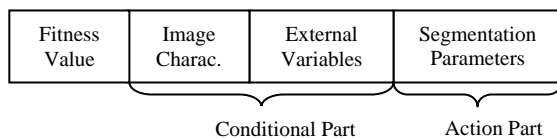


Figure 2a: Structure Knowledge used by the adaptive segmentation system.

Figure(2b) shows an example of a knowledge structure used by the adaptive segmentation system. The knowledge structure stores the current fitness of the parameter settings, the image characteristics and external variables of the image, and the segmentation parameter set used to process images with these characteristics. The image characteristics and external variables form the condition part of the knowledge structure, where the segmentation parameters indicate the actions part of the knowledge structure. The fitness, which range from 0.0 to 1.0, measures the quality of the segmentation parameter set.

Note that only the fitness value and the action part of the knowledge structure are subject to genetic adaptation, the conditions remain fixed for the life of the structure.

We assume that similar images will require similar parameters for segmentation. We are adapting to the changes in images caused by varying environmental conditions. When a new image is provided during testing phase of the adaptive segmentation, the process begins by comparing the image characteristics of the new image with the knowledge structures in the

reference population. The reference population represents the accumulated knowledge of the adaptive system obtained through previous segmentation experience. If an image and several members of the reference population are the same, fitness values are used to select the best individuals from the population. Temporary copies of the highest ranked individuals are used to create seed population for the new image.

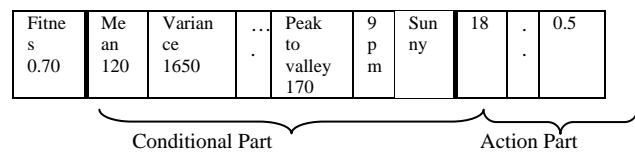


Figure 2b: Example of a Structure Knowledge used by the adaptive segmentation system.

Once the seed population is available, the genetic adaptation cycle begins. This cycle shown in figure(3). The segmentation parameter set in each member of the seed population is used to process the image. The quality of segmented results for each parameter set is then evaluated. If the stopping criteria are satisfied, the cycle terminates and the height quality members of the current image population are used to update the reference population.

Less fit members of the reference population are discarded in favor of higher-strength individuals obtained from processing the current image. In this manner, the system is able to extend the knowledge of the adaptive segmentation system by incorporating new experience into the knowledge base.

Alternatively, if after segmentation and evaluating the performance of the current population, the system has not satisfied termination criteria, the genetic recombination operators are applied to the members of the current population. The reproduction operator is first applied to select the individuals in the population on the basis of their relative fitness values. The crossover and mutation operators are then applied to the reproduced, high strength individuals, creating a new set of offspring which will theoretically yield better performance. The new population is supplied back to the image segmentation process, where the cycle begins again. Each pass through the loop (segmentation-evaluation-reproduction-recombination) is known as a *generation*. The cycle continues until the total number of generations reaches the limit. The reference

population is updated and the system is then ready to process a new image.

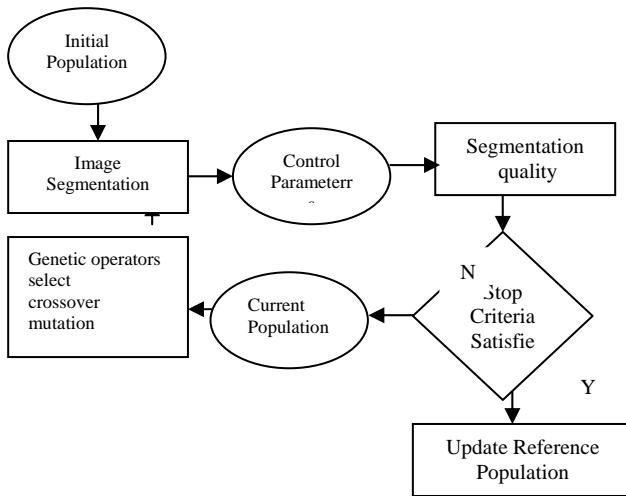


Figure 3: Genetic Adaptive Segmentation Cycle

4-3 Segmentation Quality Measures

After the image segmentation is completed, three different quality measures are used to determine the overall fitness for a particular parameter set. These measures are as follows [7,8]:-

a-Edge-Border Coincidence

measure the overlap of the region borders in the image acquired from the segmentation algorithm relative to the edges found using an edge Sobol operators.

b-Pixel Classification

measures the number of object pixels classified as background pixels and the number of background pixels classified as object pixels.

c-Discrepancy D :

A discrepancy measure depends on the classic object background problem and the classification has two unique categories - the measure is defined as:

$$D=P(O)P(B/O)+P(B)P(/B),$$

where $P(O)$ is the prior probability of a pixel being classified as belonging to an object, $P(O/B)$ is the probability of a background pixel being classified as belonging to an object, $P(B)$ the prior probability of a pixel being classified as belonging to the background, and $P(B/O)$ the probability of a pixel from an object being

considered as belonging to the background.. In the present case, the objects are the edges of the image, and the remaining pixels belong to the background. Thus,

$$P(O) = \frac{N_e}{N}, \quad P(B/O) = \frac{N_h}{N},$$

$$P(B) = \frac{N - N_e}{N}, \quad P(O/B) = \frac{N_b}{N - N_e},$$

$$D = \frac{N_e}{N} \frac{N_h}{N_e} + \frac{N - N_e}{N} \frac{N_b}{N - N_e} = \frac{N_b + N_h}{N}$$

where:-

N_b =No. of bits in the real segmented image.

N_h =No. of holes in the real segmented image.

N_e =No. of edge pixels in the ideal segmented image.

N = No. of pixels in the image.

The value for each of the three segmentation quality measures is between 0 and 1.

5-Experimental Results

1.Input Images

The original outdoor images are digitized at 480X480 pixels in size (database consists of 10 frames) collected approximately every 25 minutes over a 4 hour period using color video camera with different weather conditions (varying in light conditions and may subtle changes between the objects in the image). The overall goal is to recognize the car in the image.

2. Segmentation Parameters

The segmentation parameters are *scale parameter, color weight and compactness weight* used to control the segment quality. The scale parameter could vary from 0 to 100, and other segmentation parameters from 0 to 1.

3. Reproduction Operators

a. Selection

The expected number of times an individual is selected for recombination is proportional to its fitness relative to the rest of the population. Local tournament selection without replacement method was used, which selects the individual with the highest fitness out of randomly picked individuals, was chosen over roulette wheel selection because it could cause premature problems at earlier stages.

b. Crossover and Mutation

Crossover and mutation determine the genetic makeup of offspring from the genetic material of the parents. A **single point crossover** between the selected chromosomes was utilized to generate a new population for each generation. A good GA performance requires a high crossover probability. Thus for this work, a crossover probability of 0.85 was adopted. Mutation provides for occasional disturbances in the crossover operation by inverting one or more genetic elements during reproduction. For this work mutation probability of 0.02 was adopted.

c. Fitness Evaluation

The fitness function is obtained by combining segmentation quality measures into a single, scalar measure of segmentation quality using a weighted sum approach. Each measure is given equal weight in the summation, which maximized overall performance of the system.

4. Stopping Criteria

The stopping criteria for the genetic algorithm contain 2 conditions. If any one of the following conditions is met, the processing of current image is stopped.

a-The process terminates if 3 consecutive generations produce a decrease in the average population fitness for the current population.

b-The genetic algorithm terminates after 50 generations. This condition is contained to ensure the termination of the algorithm.

5- Basic Experiments

Experimentation on the outdoor image database is divided into two separate phases:-

1-A training phase where the optimization capabilities of the genetic algorithm are measured, and

2-A testing phase where the reduction in effort achieved by utilizing previous segmentation experience is evaluated.

The knowledge base for testing phase is obtained by collecting the final population from each of the training images to form a training population. The outdoor image sequence is separated into 2 halves: 5 images (odd number) are chosen for training and other 5 images (even numbers) are saved for testing purpose.

5-1 Training Experiment

In the training phase, random locations in the parameter space are selected as the seed population. The genetic learning algorithm is invoked using the seed population for each image and the convergence rate of the process is measured. Each training image is processed 100 times, each with a different collection of random starting points, Figure (4) shows the average number of generation for each of the outdoor training images, as well as the average number of generation for all training images as computed and maximum number of generation is 12, the minimum number is 5, and the average number of generations for the outdoor training imagery is 7.4.

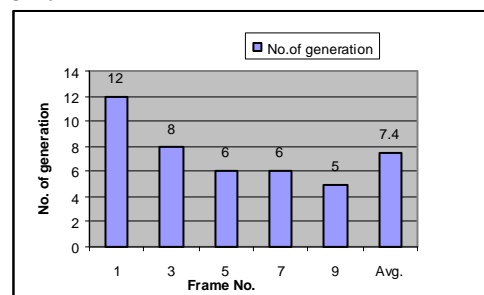


Figure 4: The graph indicate the adaptive image segmentation system optimized the segmentation quality of each training image in the number of generations.

Figure (5 a-g) show the original image and the initial and final segmentation result for some of training images (frame 3,5,9).

In particular, the portion of the car that is extracted from the image is always greater in the final result. Frame 3 or 9, the bottom of the car is extracted as a separate region from the background although this region is still not combined with the top portion of the car to form a single region.

5-2 Testing Experiments

Once the training phase of outdoor imagery experiments is complete, the testing phase began. This phase is designed to measure the reduction in effort obtained by initializing the genetic optimization process with non-random starting points. The final populations from each of the training images (1,3,5,7,9) are combined to create a reference population of 100 individuals. From this population, the 10 initial members of each seed population for the testing images (2,4,...10) are selected. Using the seed populations which are obtained from the reference population, the adaptive image

segmentation system is invoked on each of the test images (2,4,...10). Figure (6) illustrate the number of generations required to optimize the segmentation quality for the test images .It also compares the performance of the adaptive image segmentation system during the training and testing phases. As the average number of generations shows (7.4) generations during training versus 4 generations during testing, the diversity of the reference population contributes significantly to the reduction in effort of the genetic algorithm.

Figure (5.h-i) show the initial and final segmentation result for some of testing images. The improved quality of the initial segmentation results during testing are visually compared with the initial results which are acquired during training. Result for adjacent images sequences (1,2,3,4...etc.) are also compared since they are similar in overall quality. For example, the initial representation of the car region in frame 10 (figure. 5-f) is much better than the initial car region in frame 9 (figure.5-h).

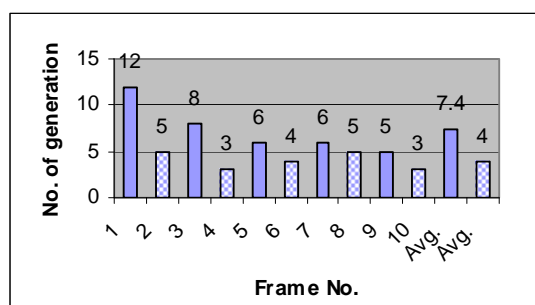


Figure 6: Comparison of training (frame 1,3,..9) and testing (frame 2,4,..10) experiment on the outdoor imagery

6- Conclusions

- 1- The adaptive image segmentation system is independent of the segmentation algorithm and its details, except for the segmentation parameters and the range of values of these parameters that they are suitably represented in the GA. The adaptive segmentation system adapts the segmentation parameters based on the quality of segmentation achieved using these parameters values.
- 2- From the graph in figure(6) the average number of generations is reduced from 7.4 during training phase to 4 during testing, equivalent segmentation performance during testing represents considerable improvement in the adaptive system's efficiency.

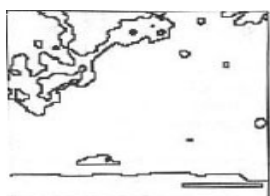
- 3- GA shows great promise in solving the parameter selection problem encountered in image segmentation task and efficiently search the space of segmentation parameters in a small number of generations.

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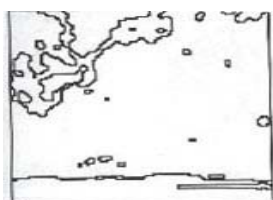
(a) Original Image



(b) Frame 3 initial Result



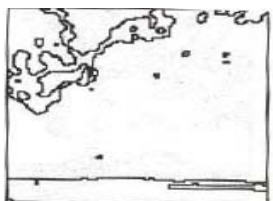
(c) Frame 3 Final Result



(d) Frame 5 initial Result



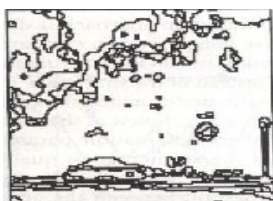
(e) Frame 5 Final Result



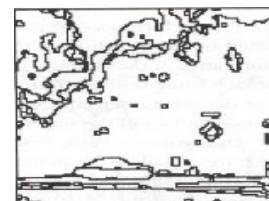
(f) Frame 9 Initial Result



(g) Frame 9 Final Result



(h) Frame 10 Initial Result



(i) Frame 10 Final Result

**Figure 5: (a) Original Image, (b-g) Segmented Images For training images frame(3,5,9)
(h-i) Segmented images for testing image frame 10.**