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Review Article

APPLICATION OF GENETIC ALGORITHM TO IMAGE SEGMENTATION: A REVIEW

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ABSTRACT

There are proves that genetic algorithms remain the most powerful unbiased optimisation techniques for sampling a large solution space. This is because the sampling strategy allows the exploration of the solution space by a strategy that is not biased. They were applied for the digital image processing like image enhancement, segmentation, feature extraction and classification as well as the image generation. The genetic procedure provides a faster convergence to the optimal solution. The constant improvement of genetic algorithms will help to solve various complex image processing tasks in the future. This paper is aimed at reviewing the application of Genetic Algorithm to image segmentation.

INTRODUCTION

Image segmentation is a low-level image processing task that aims at partitioning an image into homogeneousregions. How region homogeneity is defined depends on the application. A great number of segmentation methods are available in the literature to segment images according to various criteria such as for example grey level, colour, or texture. Recently, researchers have investigated the application of genetic algorithms (GA) into the image segmentation problem. Perhaps the most extensive and detailed work on GAs within image segmentation is that of Bhanu and Lee. Genetic Algorithms (GAs) are basically the natural selection process invented by Charles Darwin where it takes input and computes an output where multiple solutions might be taken. The GAs is designed to simulate processes in natural system necessary for evolution. GA performs efficient search in global spaces to get an optimal solution. GA is more effective in the contrast enhancement and produce image with natural contrast. A Genetic Algorithm provides the systematic random search. Genetic Algorithms provide a simple and almost generic method to solve complex optimization problems.

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A genetic algorithm is a derivative-free and stochastic optimization method. A Genetic Algorithm needs less prior information about the problems to be solved than the conventional optimization schemes. One reason (among others) for using this kind of approach is mainly related with the GA ability to deal with large, complex search spaces in situations where only minimum knowledge is available about the objective function. For example, most existing image segmentation algorithms have many parameters that need to be adjusted. The corresponding search space is in many situations, quite large and there are complex interactions among parameters, namely if we are seeking to solve colour image segmentation problems. For instance, this led Bhanu et al. to adopt a GA to determine the parameter set that optimise the output of an existing segmentation algorithm under various conditions of image acquisition. Another situation wherein GAs may be useful tools is illustrated by the work of Yoshimura and Oe. In their work, the two authors formulated the segmentation problem upon texturedimages as an optimisation problem, and adopt GAs for the clustering of small regions in a feature space, using also Kohonen's self-organising maps (SOM). They divided the original image into many small rectangular regions and extracted texture features from the data in each small region by using the two-dimensional autoregressive model (2D-AR), fractal dimension, mean.

The aim of this article is to review GA applications for the most fundamental image processing tasks – image enhancement and image segmentation. The article surveys recent and older approaches which solve optimization problems using GA as a primary optimization tool. The main ideas of such approaches are explained as well.

IMAGE SEGMENTATION

Image Segmentation is the most challenging task in image processing. The original image is separated into different pieces for better analysis. The most difficult task in image segmentation is parameter selection. The goal of image segmentation is to cluster pixels into salient image regions, i.e., regions corresponding to individual surfaces, objects, or natural parts of objects.

Importance of Segmentation

- Segmentation is generally the first stage in any attempt to analyse or interpret animage automatically.
- Segmentation bridges the gap between low-level image processing and high-level image processing.
- Some kinds of segmentation technique will be found in any application involving the detection, recognition, and measurement of objects in images.
- The role of segmentation is crucial in mosttasks requiring image analysis. The success or failure of the task is often a direct consequence of the success orfailure of segmentation.
- However, a reliable and accurate segmentation of an image is, in general, very difficult to achieve by purely automatic means.

Requirements for Image Segmentation

Good image segmentation meets certain requirements:

- Every pixel in the image belongs to a region.
- A region is connected: any two pixels in a particular region can be connected by a line that doesn't leave the region.
- Each region is homogeneous with respect to a chosen characteristic. The characteristic could be syntactic (for example, colour, intensity or texture) or based on semantic interpretation.
- Adjacent regions can't be merged into a single homogeneous region.
- No regions overlap.

Methods of Image Segmentation

Bhanu and Lee divide the image segmentation algorithms into three major categories:

- Edge Based
- Clustering Based
- Region Based

Edge Based Techniques Edges are basic features of an image, which carry valuable information, useful in image analysis object classification.

Edge detection includes the detection of boundaries between different regions of the image. Due to these boundaries discontinuities occurs between the pixels of the chosen feature such as colour, texture and intensity.

Clustering Based Techniques

Clustering separates the image into various classes which does not require any prior information. In this the data which belong to same class should be as similar as possible and the data which belongs to different class should be as different as possible.

Region Based Techniques

Region splitting is an image segmentation method in which pixels are classified into regions. Each region has a range of feature values, with thresholds being delimiters. It is very important to choose these thresholds, as it greatly affects the quality of the segmentation. This tends to excessively split regions, resulting in over segmentation.

Applications of Image Segmentation

Image Segmentation has many applications which are:

- Industrial inspection
- Optical character recognition (OCR)
- Tracking of objects in a sequence of images
- Detection and measurement of bone, tissue, etc., in medical images.
- Face and Fingerprint recognition
- Medical imaging such as:
- Locate tumors and other pathologies
- Measure tissue volumes
- Computer-guided surgery
- Diagnosis
- Treatment planning
- Study of anatomical structure
- Locate objects in satellite images (roads, forests, etc.)
- Iris recognition
- Traffic control systems
- Brake light detection
- Machine vision
- Agricultural imaging – crop disease detection etc.

Genetic Algorithms

Genetic algorithms (GAs) are adaptive search procedureswhich were first introduced by Holland, and extensively studied by Goldberg, De long, and others. Oneof the most successful areas of application has been the use of GAs to solve a wide variety of difficult numerical optimization problems. GAs complement existing optimization methods nicely in that they require no gradient information and are much less likely to get trapped in local minima on multimodal surfaces. In GAs, each possible solution within the population of abiological individual is coded in so called "chromosome"(i.e. individual). A number of chromosomes generatewhat is called a "population". The structure for eachindividual can be represented as a string of characterswhich are usually binary digits or real numbers.

Thechromosomes share data with other, and each chromosomeis assigned a fitness score according to how good a solution to the problem based on a given fitness function. The solutions are taken according to their fitness values and used to construct new solutions by a hope that the new solutions will be better than the old solutions and a generation is complete. Thus, the whole population moves like a one group towards an optimal area. At each generation, each individual is evaluated andrecombined with others on the basis of its fitness. Theexpected number of times an individual is selected forrecombination is proportional to its fitness; the fitness isrelative to the rest of the population. New individuals arecreated using crossover and mutation operations. Crossover operates by selecting a random location inthe genetic string of the parents (crossover point) andconcatenating the initial segment of one parent with thefinal segment of the second parent to create a new child. A second child is simultaneously generated using theremaining segments of the two parents. Mutation provides for occasional disturbances in thecrossover operation by inverting one or more geneticelements during reproduction.

Search Space

The space for all possible feasible solutions is called search space. Each solution can be marked by its value of the fitness of the problem. Looking for the solution means looking for extreme (either maximum or minimum) in search space. The search space can be known by the time of solving a problem and we generate other points as the process of finding the solution continues. (Shown in Fig. 1)

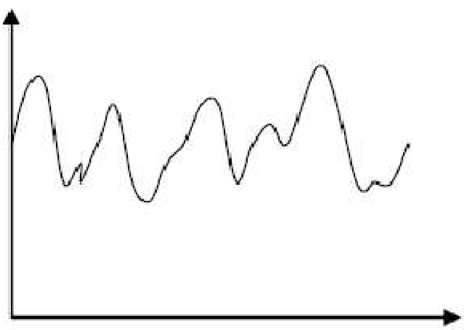

Fig. 1. Examples of search space

Genetic Algorithm Methodology

In a Genetic Algorithm, a population of strings called chromosomes which encode candidate solutions to an optimization problem evolves toward better solutions. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals arestochastically selected from the current population (based on their fitness), and modified (crossover and mutation) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached.

Genetic Algorithm procedure

A simple GA (Fig 2) consists of five steps:

- Start with a randomly generated population of N chromosomes, where N is the size of population, l – length of chromosome x.
- Calculate the fitness value of function φ(x) of each chromosome x in the population.
- Repeat until N offsprings are created:

Probabilistically select a pair of chromosomes from current population using value of fitness function.

Produce an offspring y_i using crossover and mutation operators, where i = 1, 2, …, N.

Replace current population with newly created one. 5. Go to step 2.

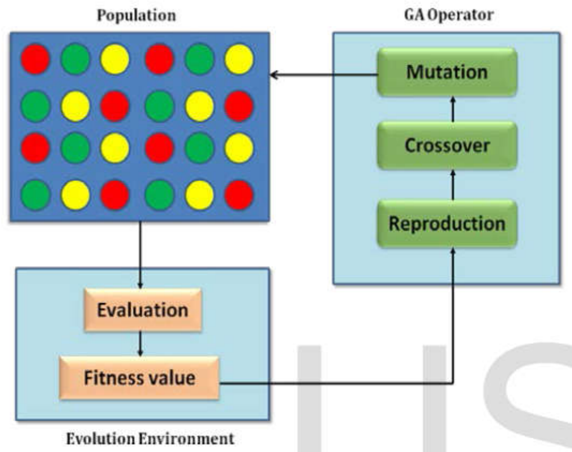

Fig. 2. Genetic Algorithm Process

Image Segmentation Using Genetic Algorithm

Each region in a segmented image has to satisfy properties of homogeneity and connectivity. The region is considered to be homogeneous if all region pixels satisfy homogeneity conditions defined per one or more pixel attributes, such as intensity, colour, texture, etc. The region is connected if a connected path between any two pixels within the region exist. If I is a set of all image pixels and H( ) is a homogeneity predicate defined over connected pixel groups, then the image segmentation is partitioning of I into connected subsets {} so that

$$\bigcup_{i=1}^{n} S_i = I \text{ and } S_i \cap S_j = \emptyset,\ i \neq j.$$

The homogeneity predicate is

$$H(S_i) = true \text{ for all } S_j,$$
$$H(S_i \cup S_j) = false \text{ for any adjacent } S_i \text{ and } S_j.$$

Computation of such image partitions has a very high combinatorial complexity. No general solution for all segmentation cases exist. Because of a very big solution space, genetic algorithms were adopted by several researchers. GA's was applied to optimize parameters of various segmentation techniques as well as to develop new techniques. One of the most fundamental segmentation techniques is edge detection.

It usually involves two stages. The first one is edge enhancement process that requires the evaluation of derivatives of the image and usage of gradient or Laplacian operators (Fig. 3). Such methods as threshold or zero-crossing produce an edge map that contains pixels candidates to be labelled as edge points of the image. But these methods provide not enough information on being a good edge. This limits their ability to exploit local edge continuity information in reducing the edge fragmentation due to noise. Furthermore, because of inherent low-pass filtering, they have a tendency to dislocate edges. To solve these problems there were various attempts taken, including different scale kernels, fitting models of edges, greedy algorithms, dynamic programming and finite element method.

Fig.3. Detected edges by using Sobel operator

The second stage involves selection and combination of edge map pixels using boundary detection, edge linking and grouping of local edges. This stage can be viewed as a search for optimal con-figuration of pixels that better approximate edges. Several approaches applied GA-based search for optimal configuration of edge pixels. Possible edge configuration S is encoded as chromosome. Each chromosome consists of a K^2 bits string, where K represents the dimension of an image I. Each bit shows the presence of an edge pixel in the image I. Algorithm evaluates each chromosome by using a cost function. The form of the point cost function is a linear combination of five weighted point factors. It includes fragmentation, thickness, local length, region similarity and curvature. These factors are evaluated for each pixel in its local neighbourhood of MXM window.

Fragmentation describes local edge discontinuities. Penalty for fragmentation is assigned to define the endpoints of the edge. Pixel is considered as an endpoint if it has only one neighbour or is isolated at all. Edge thinness penalty is assigned to edge pixels that are not thin. A pixel, in configuration S, is considered to be thin, if it is connected with any other pixel, from configuration S, by just one path. To avoid detection of excessive number of edges, there is length penalty assigned. Each edge pixel receives this penalty. This helps to eliminate pixels appearing because of noise and short and useless edge fragments. As canny edge operator assigns edge strength value, it is necessary to estimate edge dissimilarity. This penalty is computed by estimating likelihood l, and assigning cost to non-edge pixels which is proportional to dissimilarity estimated in likelihood map L. The last penalty – element smoothness, is assigned according to pixel-to-pixel connection angle. If it is 0, the penalty is also 0, if 45 degrees – 0.5 is assigned, if angle equals or is more than 90 degrees, penalty is 1. The first population of chromosomes is generated in specific way. Initial edge configurations are gene-rated from the filtered image. This is due to a very large search space. There are 2^{K2}possible solutions. Reproduction is performed by copying some portion of one chromosome to another. Mutation, ran-domly with low probability, replaces members of chromosome. The whole algorithm terminates after the cost function has remained invariant with some tolerance for one generation. This algorithm was extended by Gudmundsson et al. In their approach, each chromosome encodes only small portion of image as an 8X8 window. These windows are connected with their neighbouring windows to keep track of edges connectivity at window corners. Also, chromosomes were changed from bit strings to bit arrays. To decrease convergence time they included a special problem-based mutation opera-tor. It selects a mutation strategy from a 24 predefined mutations set.

Conclusions

GA can be used as a very promising unbiased optimization method; it constantly gains popularity in image processing. Various tasks from basic image contrast and level of detail enhancement, to complex filters and deformable models parameters are solved using this paradigm. The algorithm allows to perform robust search without trapping in local extremes. Different authors adopt GAs to solve a very big variety of simple and difficult tasks. Every approach is unique, with different information encoding types, reproduction and selection schemes. The success of optimization strongly depends on the chosen chromosome encoding scheme, crossover and mutation strategies as well as fitness function. For each problem, careful analysis must be done and correct approach chosen. As it was shown, one chromosome can contain a whole image or only a small part of it, a whole parameter range or only the most descriptive ones. Crossover can be performed in various manners, for example by exchanging information at one brake point or at several one. Different strategies may be used for genetic information transfer and parallel evolution may be adopted.

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