Object Extraction Based on Evolutionary Morphological Processing

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ABSTRACT  This paper introduces a novel technique for object detection using genetic algorithms and morphological processing. The method employs a kind of object oriented structure element, which is derived by genetic algorithms. The population of morphological filters is iteratively evaluated according to a statistical performance index corresponding to object extraction ability, and evolves into an optimal structuring element using the evolution principles of genetic search. Experimental results of road extraction from high resolution satellite images are presented to illustrate the merit and feasibility of the proposed method.

KEY WORDS  object extraction; genetic algorithms; morphological processing; high resolution satellite images

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Introduction

Automatic object extraction is usually a bottleneck in many vision processes. Because of the complexity of objects in satellite images, the object extraction in most satellite image processing systems depends on human-computer interaction mainly. The accuracy of human visual detection declines with slow, dull, endless routine jobs, and the results are expensive. Thus automatic object extraction should be obviously the alternative to the human visual detection.

This paper is concerned with the problem of automatic object extraction from satellite images using machine vision technology. Over the past years various methods have been developed to extract objects such as buildings, roads, rivers etc.\(^{[1,2]}\). However these methods mostly depend on human-computer interaction and multi-sensor data or they are only suitable for some special purposes. This paper presents a novel approach to extract objects by only using high resolution satellite panchromatic image. This approach is based on genetic algorithms and morphological processing. Mathematical morphology is closely related to integral geometry. It quantifies many aspects of the geometrical structure of images in a way that agrees with human intuition and perception. Mathematical morphology has been widely used for biomedical and electron microscopy image analyses, and it also is a valuable tool in many other image processing applications. Morphological processing can be employed for many purposes including pre-processing, edge detection, segmentation, and object recognition\(^{[3,4]}\). Morphological expressions are defined as a combination of image operations, the simplest of which is the operation of erosion and dilation. The morphological approach is based on the analysis of an image in terms of some predetermined geometric shape templates known as structuring elements. The manner in which the structuring elements can be embedded into the original shape by using a specific sequence of operators leads eventually to shape...
classification or discrimination. The morphological operators are the filters that encode the original shape lead to data compression, and provide features needed for shape discrimination. However, the structuring elements design is difficult due to its computational intractability. Fortunately, Genetic algorithm (GA) is a powerful tool to solve optimization problem. It can search for good solutions adaptively by using a collection of search points known as a population in order to maximize some desirable criterion. Therefore in this study genetic algorithms are used to learn morphology processing parameters and object segmentation thresholds. According to the characteristics of different objects, the approach is able to set different structuring elements and processing thresholds automatically. The approach can be used as a general approach of object extraction. This paper describes the detailed procedures that include encoding scheme, genetic operation and evaluation function.

The automatic object extraction approach proposed in this paper has been implemented and tested on many high resolution satellite images. The results suggest that the proposed approach is feasible.

1 Methodology

1.1 Object extraction approach based on morphological processing

Because most objects have typical shape feature, object extraction can be regarded as a procedure of shape discrimination based on grey images. As mentioned above, the morphological structuring elements can be thought of the filters that extract objects [5, 6]. Therefore, the design of structure elements is the key issue for object extraction. Usually, the structuring elements are designed manually. R. Ehrhardt presented an approach to design of structuring elements by using morphology and genetic algorithms [7]. But his approach only worked for binary image. In this paper, we present a novel design approach for morphological structuring elements, which can be used for both binary images and grey images. In addition, the approach can also learn the thresholds of object segmentation and noise removal. These will be described in the next section.

In this paper, the whole object extraction procedure is divided into two steps. The first step is the off-line learning phase, where genetic algorithms are used to extract optimal structuring element parameters, segment thresholds and noise removal thresholds through learning training images. The second step is the on-line implementing phase, where the parameters obtained by genetic algorithms in the first step are used for morphology processing. Firstly, in order to reduce computation cost, a pyramid image is generated on the basis of the original image. Then the structuring elements obtained by GA are used for top-hat operation on the pyramid image. The aim of the operation is to increase the grey value of the pixels within object region and decrease the grey value of the pixels out of object region. In other words, the operation enhances the contrast between object regions and non-object regions. Secondly, segmentation threshold is employed to extract the interested object region from the image generated by close top-hat operation. Thirdly, the threshold for noise removal is employed to remove the small regions of areas less than the threshold. After above two phases, interested objects can be extracted. Fig. 1 shows the whole object extraction procedure.

1.2 Overview of GAs

GAs are adaptive search procedures derived from the principles of natural population evolution and are recently drawing the attention as the powerful intelligent system following the neural networks and simulated annealing etc. GA is briefly characterized by three main concepts: a Darwinian notion of fitness or strength which determines an individual's likelihood of affecting future generations through reproduction, a reproduction operation which selects individuals for recombination according to their fitness or strength, and a recombination operation which
Off-line learning Phase

- Input training sets
- Learning parameters using GA

On-line implementing phase

- Input image
  - Build pyramidal image
  - Structuring element
    - Top hat operation
    - Object segmentation
    - Threshold 1
    - Threshold 2
    - Noise removal
  - Output results

Fig. 1 Proposed object extraction procedure

creates new offspring based on the generation structure of their parents. In order to solve the acquired problem, GA picks up candidate solutions as the individuals on the constraints of the problem and searches gradually within the population of individuals for the optimum solution according to the above concepts. An individual is formed in one-dimensional sequence of numerals or alphabets, etc. Each element of the individual corresponds to a gene, the possible value of the gene is the allele and the location of the gene is the locus.

The fitness of each individual is calculated from the evaluation function. Taking this fitness as a basis, evolutionary operators: crossover, mutation and selection, form new individuals gradually.

Some recent attempts in applying GAs for machine vision problem such as image segmentation, primitive extraction, scene recognition and image interpretation are reported in References [8,9]. In this study, we apply GAs to obtain optimal parameters for morphology processing.

1.3 Genetic algorithms for learning structuring elements

Basically, a genetic algorithm includes six issues including encoding scheme, evaluation, selection, crossover, mutation and stopping criterion. In this study several following issues must be considered as follows.

1.3.1 An encoding scheme

We define a set of individuals \( I \) in a population \( P \) generated during \( t \) generation cycles. \( P(t) = \{ I_k | k = 1, 2, \cdots, N \} \), where \( N \) is the number of individuals or the population size. The size affects both the ultimate performance and the efficiency of GA. Each individual is generated by some encoded form known as a chromosome.

In this study, a 9 by 9 binary structuring element is used to implement morphology processing. After morphology processing, we employ the thresholding method to distinguish interested objects and uninterested objects. Finally, an area threshold is used to remove the objects whose area is less than the threshold. Thus, the solution, the thresholds and parameters of the 9 by 9 binary structuring element, is encoded as a chromosome. The chromosome consists of 83 real numbers. The first 81 numbers represent the parameters of the filters, each number has two states: 0 or 1. The rest 2 numbers represent the segment threshold and noise removal threshold respectively. Their ranges are defined as 0-255. Fig. 2 is the detailed encoding scheme.
1.3.2 Fitness function

We need to define a function which measures the detection quality of a filter. The fitness function is defined as $\text{Fitness} = p$, where $p$ is the recognition rate of a training image, and $\bar{P}$ is the average recognition rate for all training images. And $p$ is defined as

$$p = \frac{\text{Pixel number of correct recognition}}{\text{Total pixel number of a training image}} \times 100\%$$

1.3.3 Genetic operation

For GAs, the two operations, namely, crossover and mutation, should be implemented. In this study, a single-point crossover is employed. For the single-point crossover, the crossover-point position in a string is randomly selected. Mutation is carried out by performing a random replacement operation on some randomly selected position of the parent strings.

The genetic algorithm will be iteratively performed on input sample images until a stopping criterion is met. The stopping criterion is either the percentage of the fitness function value improvement between two consecutive iteration is less than a threshold or the number of iteration is over a given threshold. Then the chromosome with the greatest fitness function value is determined.

1.3.4 System parameters

Basically, the system parameters used in GAs comprise the probability of applying crossover ($P_c$), the probability of applying mutation ($P_m$), the population size ($M$) and the maximum number of iterations ($N$) for GAs. Proper parameters can speed the searching procedure as soon as possible. According to prior knowledge, $P_c$ is 0.6, $P_m$ is 0.4, $M$ is 30 and $N$ is 50.

1.3.5 The procedure of genetic algorithms for evolving thresholds and structuring elements

The procedure of evolving thresholds and structuring elements is given below, where $P(t)$ is the population of candidate solutions of generation $t$.

$t=0$;
initialize $P(t)$
evaluate $P(t)$
while not (termination condition)
begin
  $t=t+1$;
  reproduce $P(t)$ from $P(t-1)$;
  recombine $P(t)$ by crossover and mutation operators;
evaluate $P(t)$;
end;
end while
2 Experimental results

The goal of the experiment is to extract roads from 1m resolution panchromatic forest images. Fig. 3 shows parts of two forest panchromatic images. Fig. 4 shows the images generated during the extraction procedure. In Fig. 4(a), roads have been enhanced, while other objects weakened. In Fig. 4(b), black lines show the extracted objects by using morphological processing with an optimal structuring element and a segmentation threshold. In Fig. 4(b), most roads are extracted, but some road segments are missed and the results include some noise. In order to remove these noise and pick up missing road segments, a direction oriented linking approach and small area removing method are employed. Fig. 4(c) illustrates the results after segment linking and noise removal. Obviously, the road extraction results are satisfactory.

![Fig. 3 Part images of two 1m resolution panchromatic forest images (Credit: "spaceimaging.com")](image)

(a) Images after open top hat operation

(b) Images after threshold processing

(c) Images after noise removal and segment linking

![Fig. 4 Images generated during the extraction procedure](image)

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objects. When we consider more objects, how can we do? In this paper, the focus of research is on areal objects. When the areal objects are generalized as linear objects in map generalization, how can we measure the direction similarity between the generalized objects?

Except for direction transformation factor, there are many factors which affect the similarity for spatial direction. Future work should concentrate on the integration of directional factor with others factors of spatial relations.

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3 Conclusions

In this paper we have described an approach for object extraction by using morphological processing and genetic algorithms. An optimal structuring element and thresholds for object extraction are derived by GA operations. Experimental results on 1m resolution satellite images show that proposed method can be used to extract some typical objects like roads.

We plan to further explore the same approach and to find general principle to detect various objects from high resolution satellite images.

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