Enhancement and Segmentation of Digital Image using Genetic Algorithm

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Abstract— Genetic algorithm is the type of Soft Computing method. The Genetic Algorithm (GA) is a model of machine learning which derives its behavior from a metaphor of the processes of evolution in nature. The aim is to enhance the quality of the image and to convert the image into segments to get more meaningful image and it will be easy to analyze the image using genetic algorithm. Genetic algorithm is the unbiased optimization technique. It is useful in image enhancement and segmentation. GA was proven to be the most powerful optimization technique in a large solution space. This explains the increasing popularity of GAs applications in image processing and other fields. Genetic Algorithms (GAs) are increasingly being explored in many areas of image analysis to solve complex optimization problems. This paper gives a brief overview of the canonical genetic algorithm and it also reviews the tasks of image pre-processing. The main task of machine vision is to enhance image quality with respect to get a required image perception. The GAs was adopted to achieve better results, faster processing times and more specialized applications. This paper introduces various approaches based on genetic algorithm to get image with good and natural contrast. The image enhancement is the most fundamental image processing tasks. And Image Segmentation is very difficult task. This paper includes the definition of image enhancement and image segmentation and also the need of Image Enhancement and the image can be enhanced using the Genetic Algorithm and the Image Segmentation using Genetic Algorithm.

Keywords—Genetic Algorithm, Data Mining, Moderate Resolution Imaging Spectroradiometer, Digital Orthoquod Quaterquad, Earth Orbiting System, CT, MRI and PET

I. INTRODUCTION

A digital image is represented by two-dimensional array or matrix of numbers. Digital image processing is the manipulation of images by computers. It has many applications in diverse areas such as telecommunication, medical imaging, graphic arts, remote sensing etc. In the past several years, many new digital image processing and analysis techniques have been developed. Image processing system plays a very important role in scientific, industrial, medical and space applications. Present trends indicate a continuation of the explosive growth of digital image processing applications well into the next century.

At its most basic level, digital image processing requires a computer upon which to process images and two pieces of special input/output devices: an image digitizer and an image display device. A typical image analysis system performs the following operations: (1) acquisition, (2) storage, (3) processing, (4) communication, and (5) display. The basic image processing operations consist of (1) formation, (2) restoration, (3) enhancement, (4) coding, (5) compression and (6) analysis. Digital image processing comprises a broad range of hardware, software, and components ranging from simple image enhancement to more complex processing and classification of image data.

The first step in image processing is image acquisition: the sensor system specially designed to view a scene and provide a digital representation; or conversion of image data from an existing medium into a digital format (A-D conversion) e.g. scan and digitize an aerial photograph. Each digital image formation system introduces a geometrical distortion, noise, and nonlinear transformations.

following the example. Some components, such as multi-leveled equations, graphics, and tables are not prescribed, although the various table text styles are provided. The formatter will need to create these components, incorporating the applicable criteria that follow.

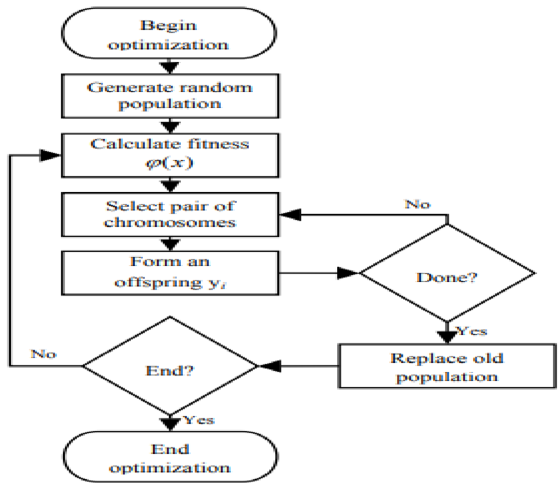

Fig 1.1 Flowchart of Image Processing

The next step deals with preprocessing of the image which typically involves procedures for image restoration and image enhancement. Digital image restoration is commonly defined as the processing of the measured image data to compensate for artifacts introduced by the image acquisition system. Digital image enhancement tries to improve the image quality by enhancing contrast, removing noise etc. Due to the fact that digital images usually require a very large amount of memory for their storage, it is very important to reduce the memory requirements for image storage and transmission. Digital image compression and coding reduce and compress the image information content by taking the advantage of the information redundancy existing in an image.

The third step deals with image analysis. Image analysis is the interpretation of the information content in an image data. It usually consists of image segmentation, image description (feature extraction), and image recognition (classification). Image segmentation partitions an input image into its constituent parts or objects. It entails division of an image into regions of similar attributes. Several methods have been developed for image segmentation including thresholding, clustering, region method, boundary detection, texture method and adaptive method. Image description, also called feature selection, involves extraction features that are basic for differentiating one class of objects from another. These features include spatial features, edges and boundaries, textures etc. Image recognition is the process that labels an object in the image based on information provided by the features. In this step, objects with identical features are grouped together under a certain class. Techniques for recognition include clustering, neural networks, decision trees, and spanning trees.

Due to the variety of application of digital image analysis, a multitude of algorithms has been presented in literature in all the areas mentioned above. Among these, algorithms for object identification and image segmentation are of prime interest. In medical diagnostic imaging, image segmentation is mainly used to process different images obtained using multiple projection methods such as CT, MRI, PET [2]. These images are used to detect tumors and other disorders. Several classical methods for image segmentation such as thresholding, clustering, edge detection and thinning have been developed for segmenting different types of images.

This paper proposes a new and simple approach for image segmentation that is based on genetic algorithm and mathematical morphology. Although GA (Genetic Algorithm) techniques have been applied extensively in optimization problems including some areas in image processing. The application of genetic algorithm in combination with morphological operation in image segmentation is investigated and the results are very encouraging.

II. EVALUATION PRINCIPLES

Numerous works deal with the problem of the evaluation of a segmentation result, [1] presents a possible classification of the evaluation criteria in three groups:

• The “analytical methods” which permit to characterize an algorithm in terms of principles, needs, complexity, convergence, stability, without any reference to a concrete implementation of the algorithm or testing data,

• The “empirical goodness methods” also called unsupervised criteria which compute a fitness metric on a segmentation result. They do not necessitate any knowledge on the segmented images to assess and their principles consist in an estimation of the quality of a segmentation result according to some statistics computed on each region, class, texture, fuzzy set... detected, mostly often by using a statistical point of view.

• The “empirical discrepancy methods” also called supervised criteria which compute some measures of dissimilarity between a segmentation result and the desired segmentation result. They thus assess the quality of a segmentation result by using an a priori knowledge. This knowledge can be a segmentation result used as a reference which is called ground truth (GT) or some knowledge on the elements to recognize.

Our center of interest is to evaluate the quality of a segmentation result; thus, the analytical criteria are not studied in this paper. Moreover, we have chosen for this study to focus on criteria which assess region segmentation results because it is a complex problem. In the next section, we study some unsupervised evaluation criteria.

III. IMAGE SEGMENTATION

Image Segmentation denotes a process by which input image is partitioned into non-overlapping regions. Each region is homogeneous and connected. The region is homogeneous if all region pixels satisfy homogeneity conditions defined per one or more pixels attributes such as intensity, color, texture etc. The region is connected if a connected path between any two pixels within the region exist. In this process the digital image can be segmented with uniform and homogeneous characteristics. The goal of image segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) [3] in images. It is the first step towards computer vision and image processing operation which includes face detection, medical imaging, locating objects in satellite images etc. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

IV. CASE STUDY

This research follows the classic evolutionary paradigm. A population of candidate solutions is evaluated by measuring their fitness with regards to a given environment. Natural selection occurs, and the survivors are allowed to reproduce. This process continues until some predefined halting condition is satisfied. This particular task is to evolve image-processing tools (“candidate solutions”) for imagery feature extraction. The environment is a set of training data. Selection proceeds using a fitness function, and reproduction is attended by crossover and mutation, with elitism available as an option. It's now discussed each component in some detail.

Considering data cube to multi-spectral data. In particular, it is considered spatially co-aligned data, so that each data plane contains the same number of pixels, and spatial information is orthogonal to spectral information. Data from different sensors and/or sensor-platforms with different spatial/spectral resolutions can be combined in principle, but we assume that the co-registration of data has already taken place and that all data planes have equal spatial resolution.

This initial work, have relied on two major sources of imagery: MODIS Airborne Simulator (MAS) data (obtained from NASA), and Digital Orthoquod Quaterquad (DOQ) data (obtained from the United States Geological Survey) [4].

The Moderate Resolution Imaging Spectroradiometer (MODIS) is an instrument designed for NASA's Earth Orbiting System (EOS) and will be the key instrument aboard the Terra (EOS AM-1) satellite (planned launch date: mid 1999). The MAS, carried by a high-altitude NASA ER-2 aircraft, simulates the full MODIS instrument, providing 50 narrow, contiguous bands of visible to infrared with 50-meter ground resolution from 20 km altitude, a wide (37.25 km) field of view, and produces 12-bit digitized data.

The DOQ data provides orthorectified aerial photography in squares of 3.75' longitude x 3.75' latitude. Panchromatic, color, and color-infrared (green/red/near infrared [0.5-0.9um]) data products are available, with approximately 1-meter ground resolution from 20,000 feet. We have used the color-infrared product, which comes in 3 band, 8-bit digitized format.

In seeking to evolve image-processing tools, the chief challenge faced by machine-learning approaches is the provision of sufficient quantities of good quality training data. That is, “ground truth” for some subset of the imagery (the training data) must be specified, either by inspection of the raw data and hand mark-up by a human analyst, or by incorporating data after actually surveying the terrain, or by application of a known algorithm. The latter case allows us to test our ability to recover known algorithms, e.g., the normalized difference vegetation index (NDVI, see e.g. [6]). Specification of the ground truth by hand can be laborious, pre-supposes that the feature of interest is known beforehand, and assumes that the feature can be identified by inspection in at least one plane of the imagery data cube.

In either case, the training data cube is augmented by what we call a truth plane. This can contain a binary mask labeling each feature pixel with a and each non-feature pixel with a 0. Alternatively, the truth “plane” may itself be composed of two or more planes to allow different weightings of pixels to guide the GA in finding the most important pixels. The truth values can be extended to byte or float type. In this way, system can evolve a feature finder that provides confidence values as well as yes-no classification.

One general feature of GP is the ability of parse trees to grow in complexity via crossover. Motivated by concerns over computational resources, it was decided to limit this growth of complexity by defining a fixed number of read/write memory (“scratch”) planes. Data planes, on the other hand, are read only, and the number of data planes in also fixed. For initial work, decided to call the final value in scratch plane A the “answer”. Evaluation of the fitness of a candidate tool depends solely on the final result it has stored in the answer plane. In general, there are several scratch planes available to a candidate tool, and it is interesting to ask what information we may find in those additional planes. To take advantage of this feature, we are currently investigating more complicated fitness evaluation schemes which would evaluate the final contents of all the scratch planes.

With this scratch plane formulation, any GP parse tree can be broken into a set of single vertex/operation sub-trees (somewhat reminiscent of [5] automatically defined functions). Results stored in a scratch plane may be reused throughout the image-processing algorithm, so actually dealing with graphs rather than trees. It was felt that this potential for reuse of intermediate results is an important capability, but also expect and find that this introduces complications for crossover, discussed. For any GP tree there exists a minimum number of scratch planes that allows representation of the tree in our scratch plane formulation.

A. IMAGE ANALYSIS PRIMITIVES

A simple notation for encoding individual genes, e.g., [ADDP, ra, rb, wA,], which reads data planes a and b, and writes the sum of these planes to scratch plane A. The final number in the block is a parameter allowing weighted sums of planes, i.e., a + p*b. referring to everything within the square brackets as the gene. Conceptually, any system such as ours is exploring the algebra of image operators. That is, how to form useful combinations of image processing operators, and how to identify the generators of this algebra. If this is to be considered in all its generality, then one is confronted by a large, unsolved problem of image analysis (for work in this direction, see, e.g., [7]). While the interested in the theoretical problem, in initial approach has been to specify a set of “useful” primitive operators and explore the space of algorithms that they generate. And chosen a set of logical, thresholding, spatial, and spectral operators, outlined in Table 1. The user can specify which operators are available in any given run.

```
Logic:          AND,
                OR,
                NOT,
Threshhold:     CLIP_HI,
                CLIP_LO,
                BOOL,
                EXPAND
                GT,
                LT,
Spectral:       ADDP,
                ADDS,
                SUBP,
                SUBS,
                MULTS,
                DIVS,
                LINSCL,
                LINCOMB,
                BANDRATIO,
                NDVI
Spatial:        MEAN,
                MEDIAN,
                ERODE,
                DILATE,
                OPEN,
                CLOSE,
                OPEN_CLOSE,
                CLOSE_OPEN
```

B. REPRESENTATION OF CANDIDATE SOLUTIONS

Chromosomes are text strings of genes,
e.g., [ADDP rb rd wA 1.0] [LT rA wC 0.23][NOP][MAX rA rb wA]
Chromosome length (measured in genes) is set at the start of a run, and is currently fixed for the duration of the run. We have included a null operator ([NOP]) to allow an effective length of less than the maximum length. We have implemented several checks to reduce unnecessary computations. In any given chromosome a number of genes will not contribute to the final answer. For example, they may write to a scratch plane other than A, that is never subsequently used. Or they may write to a scratch plane that is overwritten before the stored result is used. These “junk” genes can be effectively stripped out of the full chromosome immediately before evaluation on the training data, by a process of checking the dependency of the answer plane on the genes [8][9]. To do this, we have implemented a scheme for calculating the GP parse tree that determines the answer in scratch plane A. Genes not contributing to this tree are not evaluated. Their contents are preserved for future evolution.

C. PRELIMINARY RESULTS

For our initial attempt to evolve an image-processing algorithm, we turned to the important and well-studied problem of finding open water (rivers and lakes) amidst vegetation. A near infrared channel from our MODIS airborne simulator data set (the location is an estuary leading to the Gulf of Mexico). Clearly, on inspection, the main body of water stands out to a human observer looking at this single band. Complication arises when we try to delineate the boundary of the water, and when we try to distinguish between open bodies of water, wet fields, and clouds. Also presented is the result of a human designed algorithm [7][5] that combines comparisons of spectral channels, and simple measures of texture (standard deviations in pixel neighborhoods).
Using the output of this algorithm for our ground truth, have completed runs of GENIE with varying population size, different basis operators, varying mutation and crossover rate, and amount of training data. GENIE successfully evolved simple algorithms that match the ground truth at the >98% level. In each case, system had discovered a threshold on one of the spectral channels that segmented the image in a way that closely matched the human designed algorithm. It was evolved first with only spectral[11][12], and then with both spectral and spatial operators. Because of the nature of this particular test case, spectral operators alone were able to achieve high-fitness solutions. We also evolved spatial/spectral solution that achieved similar scores on our training and test data. In the process of expanding investigation to see how these algorithms fare with a wider range of data sets, and will investigate the suitability of these evolved algorithms as starting points for future runs.

V. FUTURE WORK

The preceding sections provide an overview of the field of image segmentation, the review shows that many current algorithms are able to produce reasonable results on images of moderate complexity; several of these algorithms are efficient enough that they can be used as a pre-processing stage for higher level vision tasks such as recognition and tracking. The [10][11]GAHSI algorithm has its own characteristics; still it has scope of improvement in adaptive adjustment of mutation rate. Elastic contour method can be improved by automatic deviation of no. of variants. In ISODATA [13][14] algorithm, a parallel cooperation with various segmentation algorithms like FCM is required for further improvement. Still, there is some scope of improvement. Reviewing the existing algorithms, we conclude that absence of prior knowledge about the image’s contents, it is in general not possible to determine how many regions are required for a reasonable segmentation. This problem manifests in two forms, Under-segmentation, which occurs when parts of the image that actually correspond to different objects, or to an object and the background, are assigned to the same region; and over-segmentation, which occurs when parts of the image corresponding to a single object are split apart.

VI. CONCLUSION

Genetic Algorithm has many advantages in obtaining the optimized solution. It was proved to be the most powerful optimization technique in a large space. Genetic algorithm allows performing robust search for finding the global optimum. The result of the optimization depends on the chromosome encoding scheme and involvement of genetic operators as well as on the fitness function. However, the quality of image segmentation can be improved by selecting the parameters in an optimized way. The desire for improvement after the GA reached a near optimal stage, led the authors to put some efforts on implementation of prior knowledge applications of GAs in clustering and grouping problems are intensively described in. In the present approach, grey level intensities of RGB image channels are considered as feature vectors, and the k-mean clustering model [9] is then applied as a quantitative criterion (or GA objective fitness function), for guiding the evolutionary algorithm in his appropriate search. In present scenario, various fast algorithms for speeding up the process of template matching are being implemented such as M-estimators for dealing with outliers. This fast algorithm ensures finding the global minimum of the robust template matching problem in which a non-decreasing Estimator serves as an error measure.

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