DIGITAL IMAGE PROCESSING: SUPERVISED CLASSIFICATION USING GENETIC ALGORITHM IN MATLAB TOOLBOX

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Abstract: Digital Image Processing (DIP) is a multidisciplinary science. The applications of image processing include: astronomy, ultrasonic imaging, remote sensing, medicine, space exploration, surveillance, automated industry inspection and many more areas. Different types of an image can be discriminated using some image classification algorithms using spectral features, the brightness and "color" information contained in each pixel. The classification procedures can be "supervised" or "unsupervised". With supervised classification, we identify examples of the Information classes (i.e., land cover type) of interest in the image. These are called *"training sites"*. The image processing software system is then used to develop a statistical characterization of the reflectance for each information class. Genetic algorithm has the merits of plentiful coding, and decoding, conveying complex knowledge flexibly. An advantage of the Genetic Algorithm is that it works well during global optimization especially with poorly behaved objective functions such as those that are discontinuous or with many local minima. MATLAB genetic algorithm toolbox is easy to use, does not need to write long codes, the run time is very fast and the results can be visual. The aim of this work was to realize the image classification using Matlab software. The image was classified using three and five classes, with a population size of 20 and time of 30, 50 and 100. The gotten results showed that the time seems to affect the classification more than the number of classes. [Report and Opinion 2010;2(6):53-61]. (ISSN:1553-9873).

Keywords: Image Processing, Genetic Algorithm, MATLAB.

1.Introduction

Image processing modifies pictures to improve them (enhancement, restoration), extract information (analysis, recognition), and change their structure (composition, image editing). Images can be processed by optical, photographic, and electronic means, but image processing using digital computers is the most common method because digital methods are fast, flexible, and precise. An image can be synthesized from a micrograph of various cell organelles by assigning a light intensity value to each cell organelle. The sensor signal is "digitized" converted to an array of numerical values, each value representing the light intensity of a small area of the cell. The digitized values are called picture elements, or "pixels," and they are stored in computer memory as a digital image. A typical size for a digital image is an array of 512 by 512 pixels, where each pixel has value in the range of 0 to 255. The digital image is processed by a computer to achieve the desired result (Rapp et al., 1996).

Digital image processing is an ever expanding and dynamic area with applications reaching out into our everyday life such as medicine, space exploration, surveillance, authentication, automated industry inspection and many more areas. Applications such as these involve different processes like image enhancement and object detection (Ross, 1994).

According to Castleman (2008), digital image processing is relatively recent in terms of humans' ancient fascination with visual stimuli. In his short history, it has been applied to practically every type of imagery, varying degrees of success. Many image processing algorithms are based on local image features, which require simultaneous access to many input image pixels, forming the neighborhood, in order to calculate the result for a single pixel of the output image (Wnuk, 2008).

Genetic algorithms (GA) integrate a young area of a research known as Evolutionary Computation. According to Castro and Von Zuben (2008), the denomination evolutionary computation was proposal in 1990 during the meeting of researchers in evolutionary algorithms in the conference of Parallel Problem Solving from Nature (PPSN) in Dortmund. However, its context is being used in a multidiscipline form, since natural sciences and engineering until biology and computer science. The basic idea is to use the natural process of evolution as a problem solution model, from its implementation in computer (Lima, 2008).

Genetic Algorithm (GA) belongs to a class of population-based stochastic search algorithm that are inspired from principles of natural evolution known as Evolutionary Algorithms (EA) (Schoenauer and Michalewicz, 1997). Other algorithms in the same

class include Evolutionary Strategies (ES), Evolutionary Programming (EP) and Genetic Programming (GP). GA is based on the principle of "survival of fittest", as in the natural phenomena of genetic inheritance and Darwinian strife for survival. In other words, GA operates on a population of individuals which represent potential solutions to a given problem, is applicable to a wide range of problem in learning and optimization (Sit, 2005).

Genetic algorithms (GA) as a non-deterministic algorithm to be natural, for the optimization of complex systems, a new Methods and proven results significantly. The digital image processing of image feature extraction, image segmentation, which are not can be avoided to produce some error. How to minimize these errors, the genetic algorithms in image processing optimization calculations are completely Competent. Current has been successfully applied to image segmentation, image classification, image reconstruction, pattern recognition and so on.

The Genetic Algorithm is a relatively simple algorithm that can be implemented in a straightforward manner. It can be applied to a wide variety of problems including unconstrained and constrained optimization problems, nonlinear programming, stochastic programming, and combinatorial optimization problems. An advantage of the Genetic Algorithm is that it works well during global optimization especially with poorly behaved objective functions such as those that are discontinuous or with many local minima. It also performs adequately with computationally hard problems (Zheng, 1999).

The surge of computer technology in the past decade has spawned numerous image processing methods. Software packages exist that are designed specifically for the task of finding particular targets in an image using various "black-box" filtering methods, the inner workings of which are hidden and irrelevant to the user. Others software allow the user to define his own mathematical method of image filtering. Image processing is most commonly done in Matlab which allows the input of strings of binary digits for manipulation with pre-defined commands.

The intent of the classification process is to categorize all pixels in a digital image into one of several land cover classes, or *"themes"*. This categorized data may then be used to produce thematic maps of the land cover present in an image. Normally, multispectral data are used to perform the classification and, indeed, the spectral pattern present within the data for each pixel is used as the numerical basis for categorization (Lillesand and Kiefer, 1994). The objective of image classification is to identify and portray, as a unique gray level (or color), the features occurring in an image in terms of the object or type of land cover these features actually represent on the ground. Image classification is perhaps the most important part of digital image analysis. It is very nice to have a *"pretty picture"* or an image, showing a magnitude of colors illustrating various features of the underlying terrain, but it is quite useless unless to know what the colors mean. The main classification methods are Supervised Classification and Unsupervised Classification.

Unsupervised classification is a method which examines a large number of unknown pixels and divides into a number of classed based on natural groupings present in the image values. Unlike supervised classification, unsupervised classification does not require analyst-specified training data. The basic premise is that values within a given cover type should be close together in the measurement space (i.e. have similar gray levels), whereas data in different classes should be comparatively well separated (i.e. have very different gray levels) (Lillesand and Kiefer, 1994; Eastman, 1995)

Supervised classification can identify examples of the Information classes (i.e., land cover type) of interest in the image. These are called *"training sites"*. The image processing software system is then used to develop a statistical characterization of the reflectance for each information class. This stage is often called "*signature analysis"* and may involve developing a characterization as simple as the mean or the rage of reflectance on each bands, or as complex as detailed analyses of the mean, variances and covariance over all bands. Once a statistical characterization has been achieved for each information class, the image is then classified by examining the reflectance for each pixel and making a decision about which of the signatures it resembles most. (Eastman, 1995).

The present research aimed to use the MATLAb Genetic Algorithm toolbox to realize the image classification using Matlab software.

2.Material and Methods

To make the classification of the imagem using Matlab software, one size population was chose (20) with three and five classes in the supervisioned classification. The time steps 30, 50 and 100 were applied with the different number of classes. The image used were digital image/photos.

2.1 Software

MATLAB is a high-level language and interactive environment that enables you to perform computationally intensive tasks faster than with traditional programming languages. It has a wide variety of functions useful to the genetic algorithm practitioner and those wishing to experiment with the

genetic algorithm for the first time. Given the versatility of MATLAB's high-level language, problems can be coded in m-files in a fraction of the time that it would take to create C or Fortran programs for the same purpose. Couple this with MATLAB's advanced data analysis, visualization tools and special purpose application domain toolboxes and the user is presented with a uniform environment with which to explore the potential of genetic algorithms.

The Genetic Algorithm Toolbox uses MATLAB matrix functions to build a set of versatile tools for implementing a wide range of genetic algorithm methods. The Genetic Algorithm Toolbox is a collection of routines, written mostly in m-files, which implement the most important functions in genetic algorithms (Sivanandam and Deepa, 2007)

2.2 Problem

To know if the different number of classes can affect the result of the classification, as well as the time steps.

3. Results and Discussion

Supervised classification is to categorise the unknown pixels into different themes, based on the spectral (or statistical) characteristics of manual-defined sampled pixels. The resultant categories and the sampled area of pixels are required to define and delineate manually. Then, the spectral characteristics of those pixels are extracted and they are being used for the classification process to classify unknown pixels in the image. After the classification process, all the unknown pixels with similar spectral characteristics of the defined categories will be assigned and pixels which have their characteristics difference from the categories will be categorised as unknown. (Lam et al., 2000). The algorithms of classification *pixel to pixel* use the individual form the spectral information of each pixel looking for homogeneous regions (Santos, 2005).

The first step of a GA is to generate an initial population of individuals characterized by their chromosomes which can be seen as possible solutions to the problem. During the evolutionary process, this population is evaluated and each chromosome receives a score, reflecting its ability to adapt to a particular environment. The fittest chromosomes are selected and the others are discarded (Darwinism). The selected individuals can suffer crossover and mutation, generating descendants for the next generation. This process is repeated until a solution found to be satisfactory.

Correa et al., (1998) had issued some considerations of using JPEG in the classification. Losses of information, degrading of sensor

performance and reducing of information contents are the disadvantages of image compression. Color is a basic feature used to extract a number of different information from an image.

In the Image 1 to 4 (Figure1, 2, 3 and 4) were used three classes to classify the images. It is possible to note that different times in some of the pictures have affected the classification maximum score. In Image1 we can notice that the time=100 was the best to classify the image because it had the maximum score (5.9931). It means the image was well classified once that this value is near 6, the maximum. In Image2 and 3, the best time shows to be the time=50 (2b and 3b), once that had the maximum score. But in Figure2 (2b) the software could not classify some pixels in the image that got the maximum score, although the results showed that it was well classified. The opposite occurs with the Image3 (3b) in which the software could classify most of the pixels. It shows accordance with the maximum score.

The Image4 had the same maximum score for all the three times (30, 50 and 100), showing that the time could not affect the classification. However the image 4a with the time=30 had most of the pixels classified while image 4b and 4c had most of the not classified by the software. So we can infer that the maximum score does not mean that we can have a big amount of pixels classified during the process.

The Images 5 to 8 (Figure5, 6, 7 and 8) were used five classes to classify the images. In Image 5 the time=30 (5a) and time=50 (5b) showed the maximum score among the times, but the image 5a had most of its pixels classified. In Image 6 the highest value was get in the time=50 was found to Image 6b while the best classification of the pixels into RGB was get in the image 6a. The image 7 (7a, 7b and 7c) had the same value for maximum score, but the time=50 and time=100 showed to be more efficient once that the software recognized most of the pixels in the image. The Image 8a had the highest value for maximum score but the image 8c had the majority of pixels classifiend during the process.

4. Conclusion

The use of different number of classes to classify an image showed not to be effective once we can note that the pixels in some of the images – same image and different classes – were not classified.

The time showed to interfere in the classification maximum score. Most of the pictures had the best time=50.

The complex and colouful images showed do not have good resolution when compared with the simple ones. During the processing of simple images the software can easy recognize the pixels.
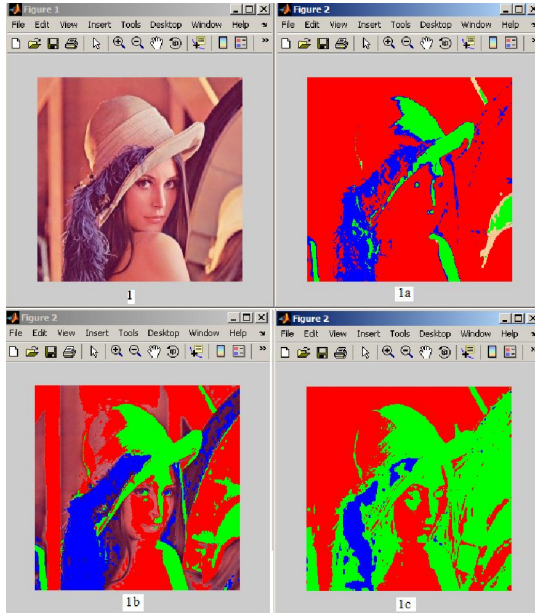
Figure Section 1

CLASSIFICATION USING THREE CLASSES

Figure1.1. Image classification using three classes (■, ■, ■). In 1 is the picture used to classify. Pictures 1a, 1b and 1c are after classification using three classes and different time 30, 50 and 100, respectively.
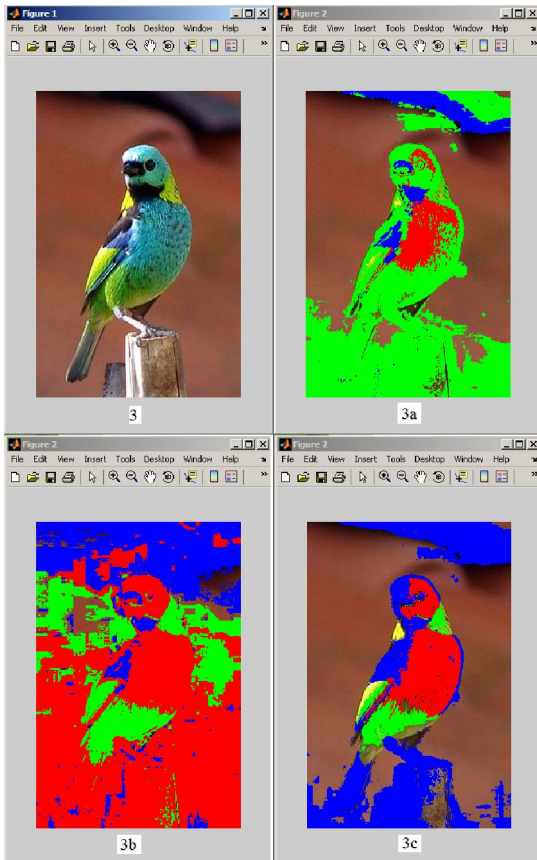

Figure2. Image classification using three classes (■, ■, ■). In 2 is the picture used to classify. Pictures 2a, 2b and 2c are after classification using three classes and different time 30, 50 and 100, respectively.

1a	1b	1c
maxScore 5.9114	maxScore 5.9861	maxScore 5.9931
maxPlace 17	maxPlace 4	maxPlace 9
time 30	time 50	time 100

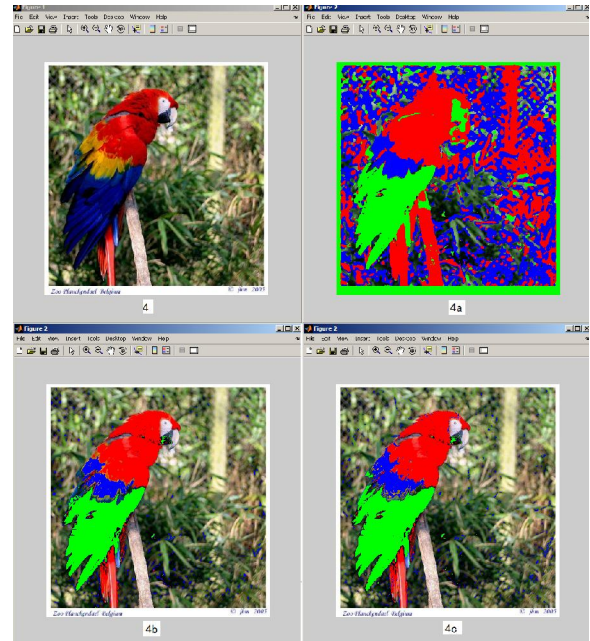| 2a	2b	2c
maxScore 5.7980	maxScore 5.8282	maxScore 5.4365
maxPlace 5	maxPlace 1	maxPlace 15
time 30	time 50	time 100

Figure3. Image classification using three classes (■, ■, ■). In 3 is the picture used to classify. Pictures 3a, 3b and 3c are after classification using three classes and different time 30, 50 and 100, respectively.

Figure4. Image classification using three classes (■, ■, ■). In 4 is the picture used to classify. Pictures 4a, 4b and 4c are after classification using three classes and different time 30, 50 and 100, respectively.

3a	3b	3c
maxScore	maxScore	maxScore
5.6466	5.8304	5.6524
maxPlace	maxPlace	maxPlace
6	3	2
time	time	time
30	50	100

4a	4b	4c
maxScore	maxScore	maxScore
5.9901	5.9901	5.9901
maxPlace	maxPlace	maxPlace
3	1	6
time	time	time
30	50	100

Figure Section 2
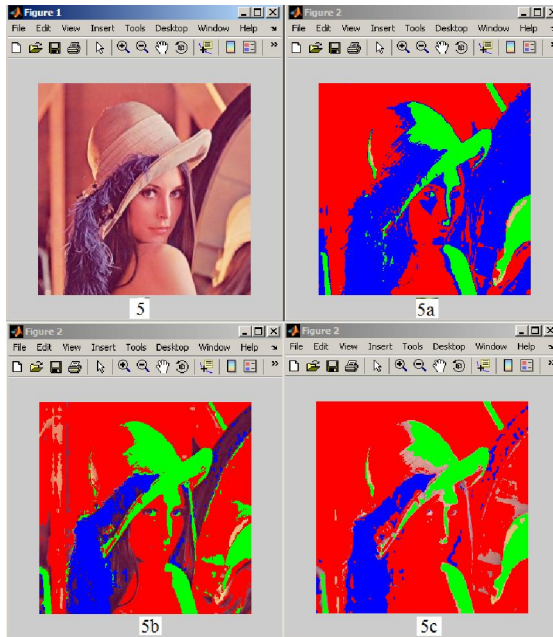
CLASSIFICATION USING FIVE CLASSES

Figure5. Image classification using five classes (, , , ,). In 5 is the picture used to classify. Pictures 5a, 5b and 5c are after classification using three classes and different time 30, 50 and 100, respectively.

5a	5b	5c
maxScore 5.9901 maxPlace 11 time 30	maxScore 5.9901 MaxPlace 20 time 50	MaxScore 5.9801 MaxPlace 16 time 100

Figure6. Image classification using five classes (, , , ,). In 6 is the picture used to classify. Pictures 6a, 6b and 6c are after classification using three classes and different time 30, 50 and 100, respectively.

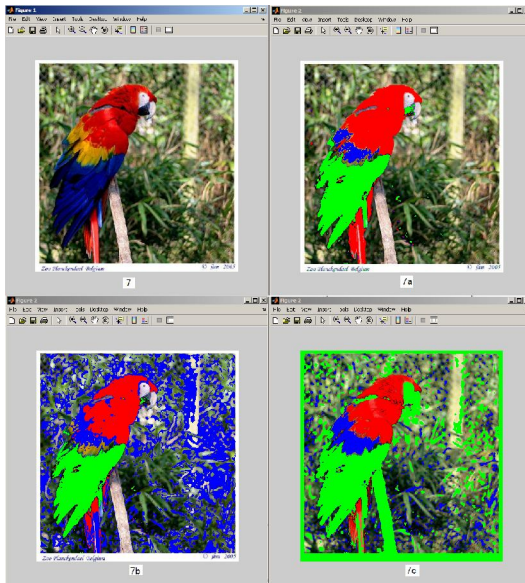| 6a	6b	6c
maxScore 5.6859 maxPlace 13 time 30	maxScore 5.9299 maxPlace 3 Time 50	maxScore 5.9194 maxPlace 12 time 100

Figure7. Image classification using five classes (▮ , ▮ , ▮ , ▮ , ▮). In 7 is the picture used to classify. Pictures 7a, 7b and 7c are after classification using three classes and different time 30, 50 and 100, respectively.

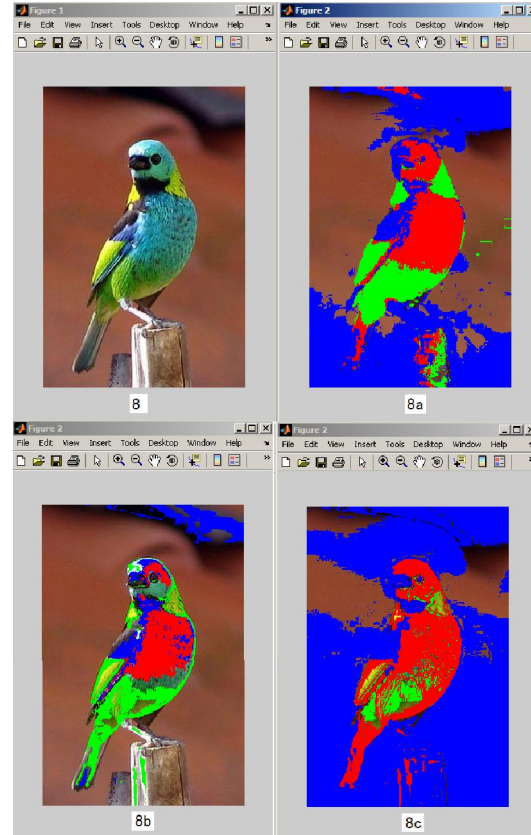| 7a	7b	7c
maxScore	maxScore	maxScore
5.9901	5.9901	5.9901
maxPlace	maxPlace	maxPlace
4	4	2
time	time	time
30	50	100

Figure8. Image classification using five classes (▮ , ▮ , ▮ , ▮ , ▮). In 8 is the picture used to classify. Pictures 8a, 8b and 8c are after classification using three classes and different time 30, 50 and 100, respectively.

8a	8b	8c
maxScore	maxScore	maxScore
5.5365	5.1929	5.1628
maxPlace	maxPlace	maxPlace
17	1	15
time	time	time
30	50	100

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