A Graphic User Interface for Images Edge Detection. A Proposal to Combine Ant Colony Systems and Fuzzy Logic

M. Angélica Pinninghoff J.
University of Concepción
Concepción, Chile
mpinning@udec.cl

Sebastián Espinoza J.
University of Concepción
Concepción, Chile
siespinozaj@gmail.com

Ricardo Contreras A.
University of Concepción
Concepción, Chile
rcontrer@udec.cl

***Abstract*—The problem of band detection in DGGE images is a key issue in biology because it allows for a correct identification of microbial populations present in biological samples. These particular images present characteristics like image distortion or the presence of noise, that affect the identification process. Traditional mechanisms for edge detection and commercial softwares only partially solve this problem. This proposal introduces a graphical interface which combines ant colony optimization and fuzzy logic to generate a map of edges for classifying pixels that are part of an edge and pixels that are not. The hybrid system is supported with an alternative matrix of pheromone and introduces an alternative set of fuzzy rules.**

***Index Terms*—graphic interface, edge detection, ACO systems, fuzzy logic**

I. Introduction

In artificial vision and in image processing, edge detection deals with the localization and identification of significant gray level variations in a digital image. Localization refers to the search of points at a particular location in a grid of pixels. Identification refers to the process of deciding whether a particular pixel belongs to an edge.

In image processing, an important number of edge detectors have been proposed, exhibiting differences in terms of mathematic and algorithmic properties [9]. One of the standard edge detection methods is proposed by Canny [7], that offers a very effective pixel identification and analyzes every pixel in the image.

Edge detection is carried out through an evaluation of the differences of pixels brightness intensities. The edge detection process is performed by evaluating differences in brightness intensity among pixels that belong to different regions in the image. A region can be characterized as edge or non-edge. It is usual to pre-process an image in such a way that the image contains only the brightness intensity information. These images are known as gray-scale images, in which every pixel holds a value between [0, 255], representing different gray intensity values, from black to white. Usual preprocessing mechanisms are edge thinning or erosion [3]. The effect of erosion on grayscale images is to erode away the boundaries of regions of foreground pixels (i.e. white pixels typically). Thus areas of foreground pixels shrink in size, and holes within those areas become larger.

Depending on the chosen method and depending on the characteristics of the image, it is possible to identify a pixel as part of an edge when the pixel is actually part of the background of the image. This problem is known as *false positive detection*. Typical characteristics of an image that lead to false positive detection are noise, blurring or lack of contrast between neighbor regions.

When dealing with brightness intensities of pixels as numerical values, it is possible to apply mathematical operations on pixels, to decide whether a particular pixel belongs to an edge. Canny algorithm, one of the best known algorithms for detecting edges, computes the gradient for a pixel (the difference of intensities among a pixels and their neighbors). The requirement of applying a gaussian filter to preprocess the image, has triggered the search for alternative methods to extend the Canny algorithm.

One of the research directions to complement the Canny algorithm, is the procedure known as *Ant Colony Optimization* (ACO), based on the ants behavior in nature [10]. ACO refers to the cooperative working of ants when foraging for food. Although communication between ants during such search is limited, the colony operates far more successfully as a whole than any individual ant within it [16]. Artificial ants manage to establish shortest routes between the colony and a food source. This capability depends upon the production of pheromones and laying of a pheromone trail by individuals ants during their search for a food source. ACO is a population-based metaheuristic that mimics the foraging behavior of ants to find approximate solutions to difficult optimization problems.

ACO has been applied to the edge detection problem, as in the work of [19]. Authors establish a pheromone matrix that represents the edge information presented at each pixel position of the image, according to the movement of a number of ants which are dispatched to move on the image. The movements of these ants are driven by the local variation of the image's intensity values.

The work of [18] proposes an approach that introduces fuzzy logic to decide, with simple rules, the ant's movements based on heuristic information, with a dynamically updated influence of the pheromone and heuristic information. Authors claim that results are improved with respect to previous experiences that use ACO. This work is important because it gives birth to a new category of edge detectors, that combines optimization through ACO and fuzzy logic inference [20]. This new category is a hybrid ACO-Fuzzy logic system.

In recent years, different researchers have explored the use of fuzzy logic in image processing. In [1] authors propose the use of fuzzy logic for the automatic analysis of X-ray images of industrial products for defect detection. The architecture is based on fuzzy logic and authors claim it is quite tolerant to imprecise input data, and therefore insensitive to noise. In [2], different implementations of the fuzzy system as an edge detector had been overviewed and compared. According to the author, the methods presented shows a better capability to recast the image to new grey level and provide a better tool to get better results in the field of the image edge detection.

In [15], Nawgaje et al. present a Fuzzy Inference System approach to detect the edges of the microscopic images within colour, which is robust and has stability degrees. They proposed the logic based technique which is a set of three pixels and, using the smallest mask of 2*2 window image, consists of a set of fuzzy rules which highlight all the edges that are correlated with an image.

In [22], authors present the implementation of a simple, flexible and efficient fuzzy logic based algorithm to detect the edges of a vehicle in an input image by scanning it through the 2*2 mask. The 2*2 masks is slid over entire vehicle image, and then pixel values of masks are examined through various rules. Based on these set of rules it is decided that particular pixel is edge or not. Peric, in [17] presents a fuzzy set based approach on edge detection, applied to region labeling, a process by which the digital image is divided into units and each unit is given a label (sky, grass, house, and so on).

In [12], authors propose a fuzzy logic based edge detection algorithm for noisy images. The proposed algorithm is based on a 3x3 window mask and fuzzy rules. The window mask and fuzzy rules are defined in a manner such as to detect edges in both noise free and noisy images. The algorithm was tested on grayscale images of size 512x512 pixels, and authors claim it detected all the edge pixels in noisy free and noisy grayscale images. Authors are currently working to extend the method to clinical examination of noisy Magnetic Resonance Images (MRI).

In [13], authors combine fuzzy logic with random walker method (a supervised segmentation method) to make resulting segmentation better in texture and quality. Fuzzy rules are used to approximate boundaries in images which improve segmentation results, when dealing with medical images. The objective of this work is to use a hybrid ACO-Fuzzy logic approach to solve the problem of edge detection on DGGE (Denaturing Gradient Gel Electrophoresis) images.

This article is structured as follows, the first section is the present introduction, the second section describes the theoretical frame supporting this work, the third section describes design and implementation issues. Section four presents results obtained and the final section shows the conclusions.

II. Theoretical frame

In this section, there is a summarized introduction to fundamental concepts involved in this work. While digital images provide the core subject, the main focus is in DGGE images. Then, there is a short introduction to fuzzy logic concepts, and the metaheuristic based on ants behavior: ACO.

A. Digital images

A digital image is a discrete representation of a two-dimensional image through the use of an image function $f(x, y)$, where x and y represent coordinates in a two-dimensional space. This function indicates the intensity or level of gray that a particular point in the image (known as pixel) presents. As x and y represent discrete locations, a matrix is the usual mechanism for representing a grayscale image.

Information that can be obtained from the matrix include the image resolution (size of the matrix, or number of pixels that define the image) and the color depth, which is the number of color values that can be assigned to a single pixel in an image. As an example, in binary images every pixel is represented by only one bit, which indicates white color, if the value is 1 and the black color if the value is 0; if we use 8 bits for each pixel, we can obtain 256 values in a gray scale ranging from 0 (representing black) to 255 (representing white). Edge pixels are pixels at which the intensity of an image function changes abruptly, and edges (or edge segments) are sets of connected edge pixels. On the other hand, edge detectors are local image processing methods designed to detect edge pixels.

B. DGGE images

Denaturing Gradient Gel Electrophoresis (DGGE) [5], [14], is a DNA-based technique which generates a genetic profile or *fingerprint* which can be used to identify the dominant members of a microbial community. DGGE has been used to investigate microbial responses in a wide variety of applications, including bioremediation assessment, wastewater treatment, drinking water treatment, biofilm formation, microbial induced corrosion, among others.

DGGE separates mixtures of amplified 16SrRNA gene segments, which are all the same size, based on nucleotide sequence. Denaturing breaks apart the two strands of the DNA molecule. Gradient Gel is a gel with an increasing concentration of a chemical (denaturant) which breaks apart the DNA molecule. Electrophoresis is the application of an electric current across a gel. In response to the current, double-stranded DNA migrates (moves down) the gel. Denaturing the DNA molecule forms Y and T-shaped structures greatly slowing migration. Finally, this process allows to obtain an image composed of bands and lanes [4].

Lanes are the vertical columns shown in Figure 1 and each one of them represents a DNA sample, except the reference lanes which are the leftmost and the rightmost lanes. Reference

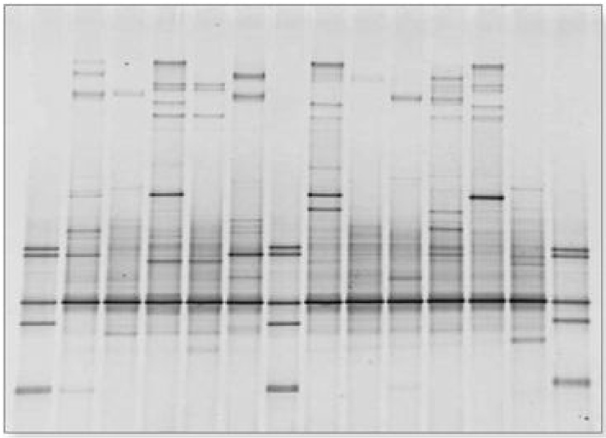

Fig. 1. A typical DGGE image.

lanes are used to indicate the molecular weight, measured in base pairs (*bp*) of the DNA.

C. Fuzzy logic

In the 60s, Zadeh [23] introduced the concept of partial set membership, to provide a reasoning mechanism that could use fuzzy variables, i.e., variables that define the language subsequently used to discuss a fuzzy concept such as temperature, pressure, age.

According to fuzzy set theory, a fuzzy set **A** on a universe of discourse **U** is characterized by a membership function $\mu_A(x)$ that takes values in the interval [0, 1]. Fuzzy sets represent commonsense linguistic values. A given element can be a member of more than one fuzzy set at a time. A fuzzy set **A** in **U** may be represented as a set of ordered pairs, with each pair consisting of a generic element x and its grade of membership function:

$$\mathbf{A} = \{(x, \mu(x)) \mid x \in \mathbf{U}\} \tag{1}$$

Knowledge is represented in the form of If ... Then rules, and these rules do not work with precisely defined values. Each variable is assigned a fuzzy value such as *high*, *moderate*, *advanced*, etc. These fuzzy values cover a range of measured values.

Our everyday language is full of fuzzy descriptors called linguistic variables. For example, height is often measured in centimeters and tall and short describe regions within this continuous scale. A linguistic variable such as age may have a value such as young, or its antonym, old. However, the great utility of linguistic variables is that they can be modified via linguistic hedges applied to primary terms. These linguistic hedges can be associated with certain functions. Being fuzzy means that there is no clear boundary between the end of one value and the start of another.

Linguistic values are context dependent, in that the range of values they are defined over depends on the variable with which they are associated. Contextual issues for any application are taken into account with a function that is defined for each linguistic variable value. The purpose of a function is to convert a measured value into a linguistic value (for example, 0 Celsius degree into *freezing*).

Fuzzy rules represent control knowledge and the task of inferencing is to map a series of input variables to a controlling output variable. The mapping from a measured value to a linguistic value is done using a fuzzy membership function. A membership function exists for each linguistic variable value, and the output of that function is a degree of membership that measures the strength of association that a measured value has with a linguistic variable [6].

D. Ant Colony Optimization

Ant Colony Optimization (ACO) algorithms are metaheuristic techniques usually applied to optimization problems. These approaches are based on the behavior of some foraging ant species, which exhibit the capability of finding the shortest path between the nest and the source of food. Ants do not show an individual behavior, but a collaborative one, under an indirect communication system, by using a specific substance, called pheromone, that ants deposit on the trails they traverse. Ants detect the presence of pheromone and tend to follow trails in which pheromone concentration is higher, which indicates that those trails have been often traversed by other ants.

This ant behavior was studied by Deneubourg [8] and based on these models Dorigo et al. [10] implemented an artificial model to emulate the ants behavior as described by Deneubourg. Results let the researches conclude that the artificial behavior of artificial ants is similar to the natural ant behavior and Dorigo proposed a derivative model for solving optimization problems [11].

Many of the computational problems that belong to the NP-hard class can be seen as optimization problems, and hence it is possible to apply ACO algorithms to obtain solutions that are close to the optimum. Typical examples are the vehicle routing problem, task assignment, and scheduling. Ant-based algorithms are also applied to telecommunications problems and industrial applications [10].

III. Design and implementation

The language chosen for development is Python in a development environment PyQt (based on Qt). The language is a software of free distribution and offers a wide library for scientific applications. At the same time, the language supports the implementation of high user-interaction applications. The software is intended for use by researchers in the Artificial Intelligence and Bioscience domains.

A. Hybrid Model

The proposed hybrid system in this work is modelled after the one proposed by Tyagi et al. [18], which incorporates ACO and Fuzzy Inference techniques in its behavior. Figure 2 illustrates the general structure of the model. The input image is subjected to grayscale conversion and gaussian filtering as part of the pre-processing stage. Later, this image feeds the Fuzzy Inference component, which characterizes the quality

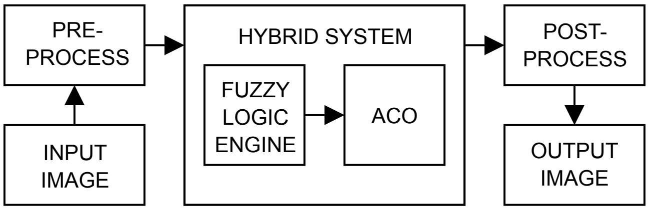

Fig. 2. General structure.

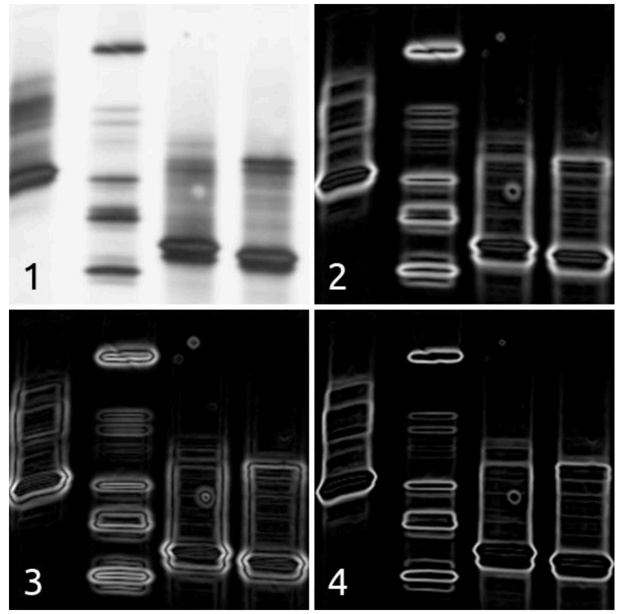

Fig. 3. Effect of substracting modified laplacian from gradient. 1: original, 2: gradient, 3: modified laplacian, 4: substraction. Note the formation of creases in the modified laplacian.

of row, column, or diagonal in its fuzzification step for each pixel in the image; this gives the name to the corresponding fuzzy variables: Mrow, Mcol and Idiag. These variables are further categorized into Low, Medium and High values, with each being modelled as a gaussian function parameterized by center (μ) and width (σ). Lastly, the fuzzy rules defined in this component determine the output image resulting from the application of a Mamdani-type defuzzification step on each pixel, where the Edgeness output variable follows the same categorization scheme as the three input variables described previously.

Once generated, the output image from the preceding stage provides the heuristic data, or Heuristic Matrix, for the ACO component in the model. In this component, a number of artificial ants (m) are randomly distributed throughout a uniformly weighted (τ_0) matrix of ones, called Pheromone Matrix, of the same dimensions as the input image. For a number of cycles (n), each ant, selected at random, moves a number of contiguous steps (s) according to the neighboring pixel (set **N**) that maximizes the value in Equation 2, where the pheromone (α) and heuristic (β) exponents vary after an ant's movement from pixel i to k depending on the difference (Δ) between the minimum and maximum values of its neighbors in the Heuristic Matrix:

$$i_{next} = argmax\left(\{\tau_k^{\alpha}\eta_k^{\beta} \mid k \in \mathbf{N}\}\right) \tag{2}$$

This movement produces a pheromone deposition in the ant's destination proportional to the corresponding value (η) in the Heuristic Matrix. The ants are randomly redistributed on the Pheromone Matrix after the end of each cycle. Finally, the process is subjected to two pheromone evaporation phases: a local one (ρ) after the step movement of each ant (Equation 3), and a global one (ψ) after the completion of each cycle (Equation 4). The output image of this stage is the resulting Pheromone Matrix.

$$\tau_i \leftarrow (1-\rho)\tau_i + \rho\eta_i \tag{3}$$

$$\tau_i \leftarrow (1-\psi)\tau_i + \psi\tau_0 \tag{4}$$

The last stage in the model is post-processing, where each pixel in the produced image is classified into border or non-border by thresholding. In line with other work using the Tyagi et al. Hybrid Model, such as [21], a modification is introduced in the form of an alternative initial Pheromone Matrix in the ACO sub-system with the intention of reinforcing the potentially relevant border regions in the image. This is done after observing the visual effect in Figure 3, where the substraction of a modified laplacian (Equation 5) from the gradient of an image (Equation 6) enhances border definition.

$$\hat{\nabla}^2(I) = \frac{d^2}{dx^2}I + 2\frac{d^2}{dxdy}I + \frac{d^2}{dy^2}I \tag{5}$$

$$\hat{\nabla}(I) = \frac{d}{dx}I + \frac{d}{dy}I \tag{6}$$

B. Interface Usage

Due to the considerable amount of parameters involved in the Tyagi et al. Hybrid System [18], a Graphical User Interface was produced to interactively execute the underlying algorithm, and observe the changes caused by the modification of said parameters. As part of a greater theme of study regarding band detection in DGGE images at UdeC, specific user requirements were stated for inclusion in the developed interface, the most critical of which being the option of segmenting the input image in slices prior to processing, and the possibility of altering the fuzzy rules and variables comprising the Fuzzy Inference sub-system.

A typical workflow of interface use is described as follows: From the Main Window, the user loads the input image into the program. If prefered, the Divide Into Bands Dialog can be summoned to divide the current DGGE image into band slices through user input, which can then be loaded into the software independently. Afterwards, the Adjust Parameters Dialog is accessed to set the number of ants to be used by the ACO sub-system, where this value can be automatically computed from

Fig. 4. Interface dialogs. Top-left: Main Window, top-right: Divide Into Bands, middle-left: Adjust Parameters, middle-right: Manage Fuzzy Rules, bottom-left: Manage Fuzzy Categories, bottom-right: Binarize Image.

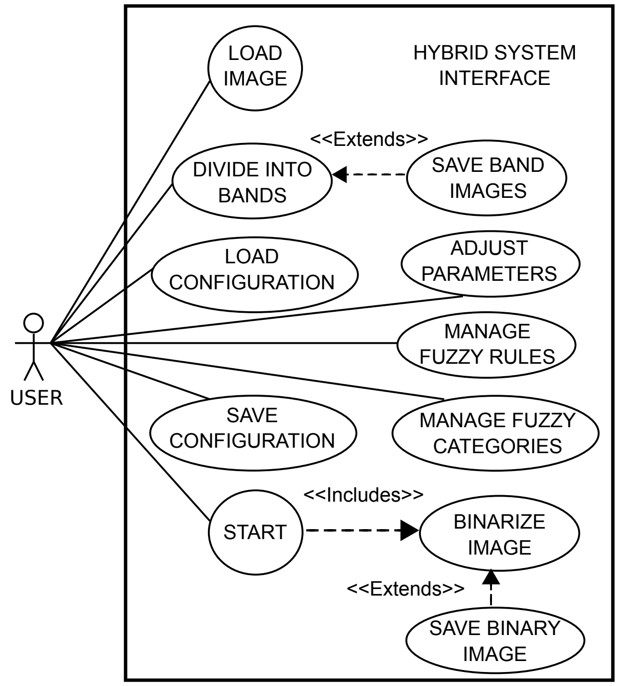

Fig. 5. Use case diagram of the hybrid system interface.

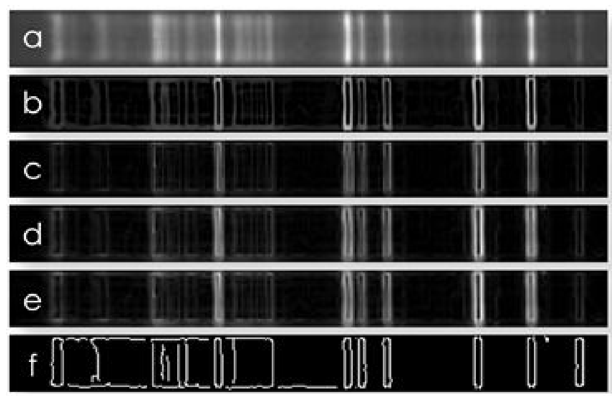

Fig. 6. Results. It takes into account different edge detection mechanisms.

the image's dimensions. Additional parameters from the ACO sub-system can be modified through Adjust Parameters Dialog, whereas fuzzy rules and categories from the Fuzzy Inference sub-system can be edited in the Manage Fuzzy Rules Dialog and Manage Fuzzy Categories Dialog, respectively. Optionally, the user may want to save the current model configuration as a file in order to retrieve it at a later time.

It is appropriate at this stage to begin executing the system by pressing the Start button from Main Window. A status bar will indicate the processing state of the program, and its completion will display the Binarize Image Dialog, where the resulting border map under the application of isodata thresholding, will be shown. Finally, the user will be able to alter the suggested thresholding value and save the generated image to a file from this same screen.

Figure 4 showcases the relevant screens of the interface, while Figure 5 presents the potential use cases encountered throughout the software's usage.

IV. Results

The system has been tested under different configurations and results are promising.

The system has been tested under different configurations, and its results are promising and similar to those obtained by using other mechanisms. The image shown in Figure 5, represents a test in which the proposed mechanism obtain a 79% of edges with respect to the best approach, proposed in [18]. Here a) is the original lane, b) shows the results obtained with the hybrid proposal, c) is the result obtained when using Roberts, d) is the result obtained when using Prewitt, e) is the result obtained using Sobel mechanism, and f) is the result obtained with Canny. Taking into account the fact that the interface allows to manage fuzzy rules an other parameters, it is possible to obtain improved results after an adjustment of parameters and rules.

V. Conclusions

The proposed interface represents an interesting alternative to detect edges in DGGE images. The alternative pheromone matrix enhances the model in a way to focus ants' search in the regions where there is a greater probability of containing edges, while providing the added benefit of obtaining leaner borders.

On the other hand, the developed interface is a very flexible tool that permits the exploration of diverse edge detection strategies within the hybrid model, as it is designed to permit the manipulation of its intrinsic parameters, as well as to readily visualize the impact these changes have upon the general behavior of the system.

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