Using Ant Colony Optimization for Edge Detection in Gray Scale Images

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Abstract. Digital image processing is a research topic that has been studied from different perspectives. In this paper we propose an approach based on a paradigm that arises from artificial life; more specifically ant colonies foraging behavior. Ant based algorithms have shown interesting results in a wide variety of situations, including optimization and clustering. In this work we compare different ant colony algorithms on a set of images, for the detection of edges. Results are presented as images, in which ants have built specific solutions, and discussed within an image-processing framework.

Keywords: Edge detection, ACO Algorithms.

1 Introduction

Digital images are two-dimensional representations of images, a set of pixels arranged in a matrix, in order to allow an electronic manipulation. In a gray-scale, each pixel is represented by using a numeric value belonging to the interval [0,255], that illustrates different shades of gray, varying from black at the weakest intensity to white at the strongest. On the other way, segmentation [9], [13] is an operation which divides an image into parts or regions having a particular feature. Segmentation algorithms are based on two intensity-based properties; the first one is the similarity among pixels, while the second one focuses on continuity related to gray levels, the last approach involves a family of algorithms for detecting edges by considering strong intensity changes among neighbors pixels. In recent years, Ant Colony Optimization (ACO) [6] algorithms have been developed to detect images' edges, by taking inspiration from the ants behavior [1], [7], [11], [16], [17].

Some ant families have the capability of finding the shortest path between their nest and the source of food. Ants use the environment as a medium for communication. They exchange information indirectly by depositing pheromone, while they pass through a particular trial (or path). The information exchanged has a local scope, only an ant located where the pheromone were left has a notion of them. This system property is called *stigmergy* and occurs in many social animal societies (it has been studied in the case of the construction of pillars in the nests of termites). The mechanism to solve a problem too complex

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to be addressed by only one ant is a good example of a self-organized system. This system is based on positive feedback (the deposit of pheromone attracts other ants that will strengthen it themselves) and negative feedback (dissipation of the route by evaporation prevents the system from thrashing). Theoretically, if the quantity of pheromone remained the same over time on all edges, no route would be chosen. However, because of feedback, a slight variation on an edge will be amplified allowing thus the choice of an edge. The algorithm will move from an unstable state, in which no edge is stronger than another, to a stable state where the route is composed of the strongest edges. The basic philosophy of the algorithm involves the movement of a colony of ants through the different states of the problem influenced by two local decision policies, viz., trails and attractiveness. Thereby, each such ant incrementally constructs a solution to the problem. When an ant completes a solution, or during the construction phase, the ant evaluates the solution and modifies the trail value on the components used in its solution.

The above described behavior is the inspiration source for using artificial ants [6], aimed to solve optimization problems.

The idea of using artificial ants to solve hard problems has been developed by different authors. In [11] is proposed an ACO algorithm hybridized with 2-OPT for fractal image compression. In [10] ACO algorithms are used in image segmentation, improving thresholding algorithms. Thresholding algorithms are the focus in [10], authors obtain experimental results to demonstrate that the proposed ant-based method performs better than other two established thresholding algorithms.

Related to previous work, closer to our proposal, in [1] authors use an ACO algorithm for image edge detection. Edge detection is accomplished by seeking pixels that show important differences with respect to their neighbors, in terms of intensity level (in gray-scale).

The work described in [17] presents an approach that obtained interesting results. They utilize a number of ants moving on a 2-D image for constructing a pheromone matrix, each entry of which represents the edge information at each pixel location of the image. The movements of the ants are steered by the local variation of the image's intensity values.

In [16] authors propose an ant colony optimization based algorithm for continuous optimization problems on images like image edge detection, image compression, image segmentation and structural damage monitoring in image processing. They show the feasibility of the algorithm in terms of accuracy and continuous optimization. This work emphasizes an important feature: a good solution, like the shortest path, has more pheromone than the longest paths.

The objective of this work is to evaluate the effectiveness of different ACO algorithms, in edge detection. In particular, this article focuses in gray-scale images. Our approach differs from the works in [7], [1] and [17], because they consider only one Ant Colony algorithm, and we take into account a set of two algorithms: Ant System (AS) and Elitist Ant System (EAS). Additionally, we compare the obtained results with the deterministic *Canny* procedure.

This article is structured as follows; the first section is made up of the present introduction; the second section describes the images (RAPD). The third section describes the ACO algorithms we used. The fourth section shows the results we obtained, and the final section shows the conclusions of the work.

2 RAPD Images

Randomly Amplified Polymorphism DNA (RAPD) images are grey scale images composed by lanes and bands, which has been used in verifying genetic identity. The 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.

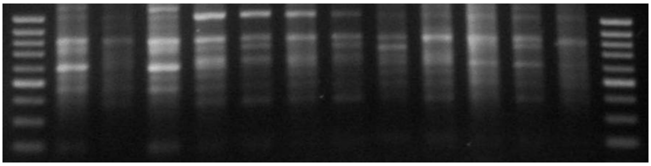


Fig. 1. A sample RAPD image with two reference lanes

The reference lanes are used to indicate the molecular weight, measured in base pairs (*bp*), of the DNA. The bands are the horizontal lines in each lane that represent the segments agglomeration of a DNA sample with the same *bp* value (see Figure 2).

Fig. 2. A sample of a lane in a RAPD image

The process of producing RAPD images is affected by many physical-chemical factors [14], and generates different kind of noise, deformations and diffusion, among others, in the lanes and bands of the RAPD images. To correct these problems is important, because their effects can lead to erroneous biological conclusions.

The RAPD image correction is a research field not completely explored. There are software tools like ImageJ [3], Gel Compar II[1], GelQuant [5] and Quantity One [2] used for RAPD image analysis. However, the correction is done manually by an expert so the abnormalities remain undetected to the human eye. This fact is pointed out in [14] where the authors use the Radon transform to correct the whole image, and mathematical morphology with cubic spline smoothing for band detection. On the other hand, in [15] is proposed a polynomial algorithm to support Multilevel Thresholding. [8] adopts that polynomial multilevel thresholding algorithm to identify the bands in a lane, however it was not possible to get a successful detection in band location. This problem acts as a reason for finding a mechanism to detect the bands, and in doing so we propose the use of different ACO algorithms.

3 ACO Algorithms

In this work, two algorithms which consider ACO were implemented. They are based on [7] and the first one employs an Ant System (AS) algorithm and the second one corresponds to an Elitist Ant System (EAS). They are based on the AS algorithm [6], and they are adapted for the specific problem.

In the AS algorithm, artificial ants walk through a space of solutions represented as a graph $G = (V, E)$, where V is the set of nodes and E is the set of edges or connections between nodes. Edges of the graph are the places where ants deposit pheromone. For implementing this model, the space of solutions is represented by a matrix of pixels of an image. Each pixel is a matrix entry, an edge in the graph represents a neighborhood between two pixels.

In ACO algorithms, an arbitrary number of ants are randomly distributed on the matrix pixels. When an ant walk through the image, it deposits pheromone. The amount of pheromone depends on the contrast among neighbor pixels. High contrasts implies more pheromone. This is reflected in the matrix, by increasing the amount of pheromone in those pixels that present some degree of intensity contrast with respect to the previous pixel in an ant movement. A higher contrast implies a higher amount of pheromone on the destiny pixel.

In this scheme, a solution is a configuration that results from the fact that every pixel in the original image has been traversed, and different regions in the image present different gray-scale intensities, due to different pheromone deposits. When a solution is obtained, it is followed (in practice, after a time interval) by a process in which the pheromone is diminished, representing the effect of the time on the pheromone that was deposited in the different paths. This process, besides to model closely a real phenomena occurring with ants, allows to avoid the effect of local minimum.

In this approach, the amount of pheromone T deposited by an ant k on each edge is given by equation (1), where η and p are constants and Δ_{gl} is the difference computed as the median intensity among the previous node and its neighbors, and the median intensity among the current node and its neighbors. Finally

[1] Details are available at `http://www.appliedmaths.com/gelcompar/gelcompar.htm`

q is a constant value, fixed in 255, that represents the maximum brightness for a pixel. It allows to deposit more pheromone in higher contrast regions in the image.

$$T_k = \eta + \frac{p\Delta_{gl}}{q} \tag{1}$$

The neighborhood of a pixel i comprises the 8 pixels (nodes) around pixel i in an image. When the pheromone is deposited, the ant moves to a new position, in a probabilistic way, taking into account the path traversed by the ant and the amount of pheromone (the intensity) in neighbors cells. The probability that an ant located at node (cell) i moves to node j is shown in equation (2) where two weights are considered: $W(\tau_{i,j})$ described in equation (3), that represents the impact of pheromone, where $(\tau_{i,j})$ is the amount of pheromone associated to the path (i,j), and $w(dir)$ that determines the weight associated to the direction that an ant can take, depending on the previous path that this ant has traversed.

Figure 3 illustrates a set of values associated to the probability, of choosing a particular path.

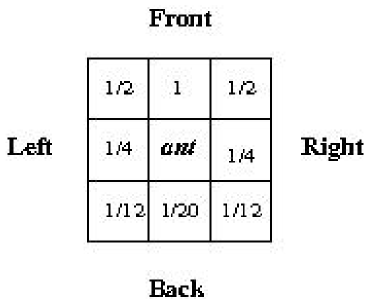


Fig. 3. Values associated to different possible paths

For $w(dir)$ we used the values suggested in [7]: $w(Front) = 1$; $w(Front - Diagonal) = 1/2$; $w(Right, Left) = 1/4$; $w(Back - Diagonal) = 1/12$; and $w(Back) = 1/20$.

Where *Front* denotes that an ant walks straightforward, keeping the previous direction in a path, *Front-Diagonal* denotes a diagonal path that combines a right (or left) movement with a front movement and *Back-Diagonal* denotes a diagonal path that combines a right (or left) movement with a back movement; *RightLeft* denotes a movement that changes the current direction to the left or to the right, and *Back* indicates the ant chooses go back, to the previous step in its traversal. It reflects the fact that the highest value is assigned to the ant walking straightforward, and the lowest value is assigned when the ant chooses to move going back through the path that has been just traversed.

$$P_{ij} = \frac{W(\tau_{i,j})w(dir)}{\sum_{l/j\epsilon N_i} W(\tau_{i,l})w(dir)} \tag{2}$$

N_i denotes the set of neighbors nodes for node i.

$$W(\tau_{i,j}) = (1 + \frac{\tau_{i,j}}{1 + \delta \cdot \tau_{i,j}})^{\beta} \tag{3}$$

In equation 3, β is a constant used to control the attraction effect that the pheromone has on the ants; δ is another constant that indicates the capability of ants to detect the pheromone.

EAS [6] differs from AS in the fact that there is a reinforcement of pheromone in edges corresponding to the best solution found in one iteration. In this case, the pheromone reinforcement is accomplished by taking into consideration the path traversed by the the ant that detects the highest differences of intensity. The amount of deposited pheromone is given by equation 1.

Canny algorithm is a well known method used for edge detection. Even though is quite old, it has become one of the standards edge detection methods [4]. The steps in the Canny edge detector are as follows: smooth the image with a two dimensional Gaussian; take the gradient of the image; non maximal suppression and edge thresholding [12].

Given the characteristics of the Canny algorithm, it is interesting to compare the results using this algorithm with the results obtained using ants. Specifically, we compare results using Canny with results using AS and EAS.

4 Results

For testing we used a set of jpg images, in gray scale, having different sizes, measured in pixels.

In AS and EAS algorithms, we considered different values for three parameters: initial population, pheromone evaporation rate, and the value that considers the variable pheromone deposit (q in equation 1). Besides that, some tests were carried out to determine the number of iterations required to obtain the maximum contrast in an image.

The other parameters were selected based on the work of [7], and these are the following: β=3.5, δ=0.2, η=0.07, p= 1.5.

In figures 4, 5 and 6 we show the images that presented the best results.

For all images: a) original image; b) image processed with AS algorithm, 500 iterations, population size equal to 30% of size image (in pixels), pheromone evaporation rate equal to 0.015; c) image processed with EAS algorithm, 1100 iterations, population size equal to 30% of size image (in pixels), d) Canny.

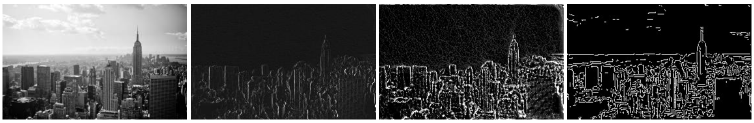
According to results, the best tested parameter combination corresponds to the image processed with the EAS algorithm, after 600 iterations, population size of 30% with respect to the original image and pheromone evaporation rate equal to 0.015. The difference can be produced by the fact that in this approach the pheromone is reinforced in the edges corresponding to the best solution for each iteration, in other words, in those places in which there is a high intensity change between pixels. It means that the pheromone concentrates on edges from the beginning of the process. On the other side, the other considered algorithms encourage, in general, the search of alternative paths.

(a) Lena (b) AS (c) EAS (d) Canny

Fig. 4. Tests with Lena

(a) Cat (b) AS (c) EAS (d) Canny

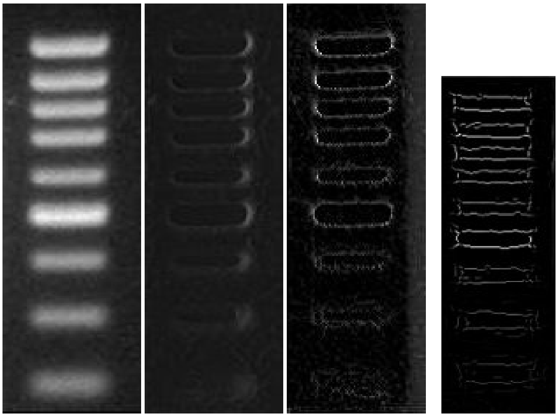
Fig. 5. Tests with cat



(a) New York (b) AS (c) EAS (d) Canny

Fig. 6. Tests with New York images

Results obtained with RAPD images were worse than expected, due to the low quality of some images. This issue made necessary an image pre-processing. During this pre-processing the contrast was increased and the image was binarized. To binarize an image allows us to obtain less fuzzy regions for helping in edge detection. In an ordinary gray-scale image, the process of detecting edges can led to non precise results. Some of obtained images are shown in Figure 7, where a) original image; b) image processed with AS algorithm, 500 iterations, population size equal to 30% of size image (in pixels) pheromone evaporation rate equal to 0.015; c) image processed with EAS algorithm, 600 iterations, population size equal to 30% of size image (in pixels), pheromone evaporation rate equal to 0.015.



(a) lane (b) AS (c) EAS (d) Canny

Fig. 7. Tests with RAPD images

In some cases, when dealing with low contrast images, some details are not detected by ants (see the image for New York city in figure 6). Ant-based algorithms cannot detect clouds in the picture, but Canny can do it. In the case of *Lena* (figure 4), where we can observe a well defined gray-scale shade, ant-based algorithms get lines with a high degree of continuity, and detect edges that can't be detected using Canny; in particular in the hair of Lena. In the case of the image for *Cat* (figure 5), we find some difficulties, because of the white color that makes edges difficult to detect.

With RAPD images, in spite of obtaining a poor result, it was possible for ant-based algorithms to detect all bands present in the image. Canny allows to detect all bands too, but edges are not clear, as it can be seen in figure 7.

For this kind of images it is necessary to continue with the experimental process, searching for new parameter combinations.

In general, EAS algorithms exhibited acceptable results, due to the fact that there is a pheromone reinforcement in candidate solutions generated by the ants. Anyway, it is important to find an equilibrium point to reflect the trade-off between the pheromone evaporation rate and the amount of pheromone an ant deposits. As with many parameters it must be done experimentally.

5 Conclusions

In this paper we have carried out a series of experiments involving ants as a mechanism for edge detection. It is clear that results obtained are improved when there is a reinforcement of pheromone for promising solutions. Shade differences are also important when detecting edges, with a uniform light distribution, as in the case of the image with the cat, the process of detecting edges is not particularly successful.

RAPD images are complex, end even the use of a standard method cannot guarantee good results, particularly due to the lack of contrast in the available images. To take into account, as a future work, we suggest to test new pre-processing methods, before applying ant-based algorithms.

References

1. Baterina, A.V., Oppus, C.: Image Edge Detection Using Ant Colony Optimization. International Journal of Circuits, Systems and Signal Processing 10(2) (2010)
2. Bio Rad Laboratories. Quantity One User's Guide. Bio-Rad Laboratories (2000)
3. Burger, W.: Digital Image Processing with Java and ImageJ. Springer (2006)
4. Canny, J.: A Computational Approach to Edge Detection. IEEE Transactions on Pattern Analysis and Machine Intelligence PAMI-8(6) (November 1986)
5. Das, R., Laederach, A.: GelQuant User's Manual. Stanford University (2004)
6. Dorigo, M., Stuetzle, T.: Ant Colony Optimization. The MIT Press (2004)
7. Fernandes, C.M.: A Camera Obscura for Ants. In: Sigevolution, Newsletter of the ACM Especial Interest Group on Genetic and Evolutionary Computation, vol. 3, pp. 9–16 (2008)
8. Carolina Gárate, O., Angélica Pinninghoff, J.M., Ricardo Contreras, A.: Band Correction in Random Amplified Polymorphism DNA Images Using Hybrid Genetic Algorithms with Multilevel Thresholding. In: Ferrández, J.M., Álvarez Sánchez, J.R., de la Paz, F., Toledo, F.J. (eds.) IWINAC 2011, Part II. LNCS, vol. 6687, pp. 426–435. Springer, Heidelberg (2011)
9. Gonzalez, R.C., Woods, R.E.: Digital Image Processing, 3rd edn. Pearson/Prentice Hall, Upper Saddle River (2008)
10. Malisia, A., Tizhoosh, H.: Image Thresholding Using Ant Colony Optimization. In: The 3rd Canadian Conference on Computer and Robot Vision, CRV 2006 (2006)
11. Martinez, C.: An ACO algorithm for image compression. CLEI Electronical Journal 9(2), paper 1 (2006)
12. Nabernehad, E., Sharifzadeh, S., Hassanpour, H.: Edge Detection Techniques: Evaluation and Comparisons. Applied Mathematical Sciences 2(31), 1507–1520 (2008)
13. Phillips, D.: Image Processing in C, 2nd edn. R & D Publications (1994)
14. Rueda, L., Uyarte, O., Valenzuela, S., Rodriguez, J.: Processing Random Amplified Polymorphism DNA Images Using the Radon Transform and Mathematical Morphology. In: Kamel, M.S., Campilho, A. (eds.) ICIAR 2007. LNCS, vol. 4633, pp. 1071–1081. Springer, Heidelberg (2007)
15. Rueda, L.: An Efficient Algorithm for Optimal Multilevel Thresholding of Irregularly Sampled Histograms. In: da Vitoria Lobo, N., Kasparis, T., Roli, F., Kwok, J.T., Georgiopoulos, M., Anagnostopoulos, G.C., Loog, M. (eds.) S+SSPR 2008. LNCS, vol. 5342, pp. 602–611. Springer, Heidelberg (2008)
16. Kaur, S., Agarwal, P., Rana, R.S.: Ant Colony Optimization: A Technique used for Image Processing. International Journal of Computer Science and Technology 2(2) (June 2011)
17. Tian, J., Yu, W., Xie, S.: An ant colony optimization algorithm for image edge detection. IEEE Congress on Evolutionary Computation (2008)