Edge detection in Images with multiplicative Noise by using Ant Colony System

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Abstract
We propose a method for edge detection in images with multiplicative noise based on Ant Colony System (ACS). To adapt the Ant Colony System algorithm to multiplicative noise, global pheromone matrix is computed by the Coefficient of Variation. We carried out a performance comparison of the edge detection Ant Colony System algorithm among several techniques, the best results were found in the gradient and the coefficient of variation.

1. Introduction

The extraction of features in images with noise is one problem difficult to solve, above all if the noise present is the noise multiplicative, one of the most aggressive [1] and [6].

The algorithms that currently used as the Coefficient of Variation (CV) [2] and [7] do not give good solutions, so we must pay attention to other algorithms.

One of these algorithms is the algorithms bioinspired, which are adaptations of the behavior, reasoning, and solution of problems of systems biological present in nature. A bioinspired algorithm is Ant Colony System (ACS) [3].

In this paper, an adaptation of the ACS algorithm is proposed to detect edges in images with multiplicative noise at various levels, also some results of experiments on a synthetic image are also presented. In the end, it is analysed qualitatively, with visual observation, and quantitatively using a performance function [5].

2. The Ant Colony System

The ACS was proposed in one principle as a solution to the traveling salesman problem (TSP) [3]. The instructions of ACS can be summarized below:

- Determine the number of ants "m" in the colony, and the number of iterations of the algorithm "n".
- For each iteration and for each one of the ants of the colony, is made following sub instructions:
  - Apply the State Transition Rule.
  - Store the visited city in a list called a Taboo List.
  - Apply the Pheromone Local Update Rule.
- Apply the Pheromone Global Update Rule.
- At end of the last iteration will you get the route more cuts.

3. Adaptation of Ant Colony Algorithm for Edge Detection

To be able to detect contours using ACS first, we must define the type of neighborhood, which for our experiments is the neighborhood of Von Neumann as is shown below.

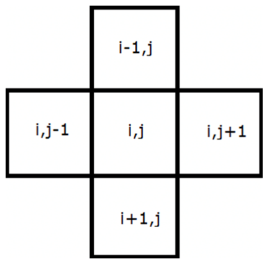


Figure 1: Neighborhood Von Neumann.

Also, must make some modifications to be able to adapt ACS for the detection of contours, these changes are:

- The edge detection in images is preserved the States Transition Rule, but it modifies the function of visibility.
- It preserves the Pheromone Local Update Rule.
- In the Pheromone Global Update Rule, only it replaces part of the expression with one constant [4].

In the end, the result to be obtained in the processing of an image using ACS is the path of the ant colony that is stored in a matrix called the Pheromone Matrix, which when thresholding we obtain an estimate of the image edge.

Two types of pheromone are defined in ACS: the first is the Global Pheromone (GF) and the second is the Local Pheromone (LF). FG is defined by one equation, the second is calculated to through of the path of the ants.

For our solution, we will use more than one FG, since we want to obtain the best contours of an image with multiplicative noise.

The first GF used is the gradient [4], which is:

$$|G(I)| = \sqrt{\frac{\delta I^2}{\delta x} + \frac{\delta I^2}{\delta y}}$$

Where $\frac{\delta I}{\delta x}$ is the partial derivate of the image I with respect to x and $\frac{\delta I}{\delta y}$ is the partial derivate of the image I with respect to y.

It should be mentioned that to obtain the result more optimal, they are used four types of gradient denominated: Gradient A (GA), Gradient B (GB), Gradient C (GC), and Gradient D (GD).

The second GF to use is the CV, which is expressed below:

$$CV(I) = \frac{\sigma}{|\overline{x}|}$$

Where σ is the standard deviation, and $|\overline{x}|$ is the absolute value of the average. Both are computed on the neighborhood defined in figure 1 of the image I to be processed.

4. Experiments and Results

In order to carry out the experiments, we will use a synthetic image and its terrain of truth, where the first is an image built from a tool, free of noise and the second is the true contours of the image. The image synthetic is contaminated to with noise multiplicative in three levels: level low of noise, level medium noise, and a level high of noise, as is shown below:

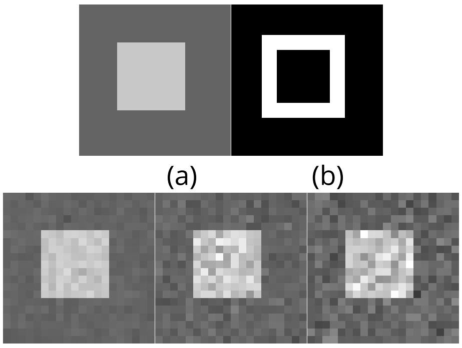
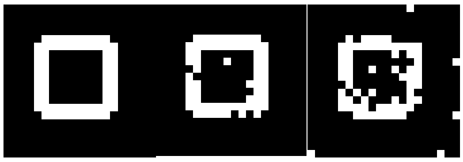


Figure 2: Simple Synthetic Image: (a) Image Original, (b) Ground of Truth, (c) Level low of noise (σ = 0,05), (d) Level medium of noise (σ = 0,1) and (e) Level high of noise (σ = 0,15).

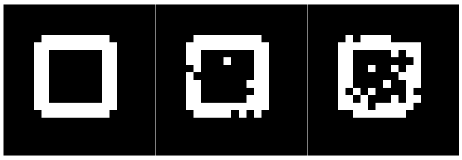
In the experiments, the ACS parameters proposed in [3] are declared. The detail of these parameters is the following: the number of ants "m" is considered one percent of the area of the image, and the number of iterations "n" is the maximum between the width and length of the image. The values of the parameters remaining are $\tau_{ini} = 1, \alpha = 1, \beta = 1, \rho = 0.3\ y\ \lambda = 0.5$.

In Figures 3, 4, 5, 6, and 7 are shown the contours detected, where: Figure 3 GF of the GA (GF-GA), Figure 4 GF GB (GF-GB), Figure 5 GF of the GC (GF- GC), figure 6 GF of the GD (GF-GD) and figure 7 GF of the CV (GF-CV).



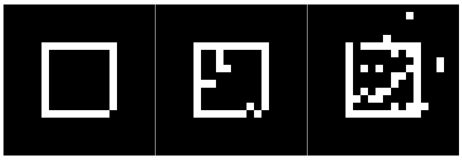
(a) (b) (c)

Figure 3: Edge detected in one image synthetic: (a) Level low of noise GF-GA, (b) Level medium of noise GF-GA, (c) level high of noise GF-GA.



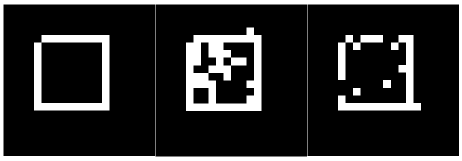
(a) (b) (c)

Figure 4: Edge detected in one image synthetic: (a) Level low of noise GF-GB, (b) Level medium of noise GF-GB, (c) level high of noise GF-GB.



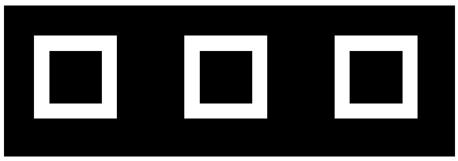
(a) (b) (c)

Figure 5: Edge detected in one image synthetic: (a) Level low of noise GF-GC, (b) Level medium of noise GF-GC, (c) level high of noise GF-GC.



(a) (b) (c)

Figure 6: Edge detected in one image Synthetic: (a) Level low of noise GF-GD, (b) Level medium of noise GF-GD, (c) level high of noise GF-GD.



(a) (b) (c)

Figure 7: Edge detected in one image synthetic: (a) Level low of noise GF-CV, (b) Level medium of noise GF-CV, (c) level high of noise GF-CV.

As can be seen, as noise increases there are more errors in contour detection. Notwithstanding the foregoing, in GF-CV fewer errors are visually obtained.

To quantify this analysis, we will use a performance function defined in [5] whose results are shown in the following tables:

Level low of noise					
	GF-GA	GF-GB	GF-GC	GF-GD	GF-CV
Optimal performance	0.95	0.95	0.48	0.48	1
Optimal threshold	0.53	0.53	0.42	0.46	0.56

Table 1: Optimal values of the performance function for level low of noise.

Level medium of noise					
	GF-GA	GF-GB	GF-GC	GF-GD	GF-CV
Optimal performance	0.83	0.85	0.44	0.47	1
Optimal threshold	0.52	0.54	0.58	0.44	0.64

Table 2: Optimal values of the performance function for the level medium of noise.

Level high of noise					
	GF-GA	GF-GB	GF-GC	GF-GD	GF-CV
Optimal performance	0.66	0.7	0.45	0.44	1
Optimal threshold	0.51	0.5	0.41	0.56	0.68

Table 3: Optimal values of the performance function for the level high of noise.

The results of the tables confirm the seen in qualitative analysis, that the GF-CV has better results in comparison to GF with the four types of gradients.

5. Conclusion and Future Works

It has proposed one method of edge detection in images with noise multiplicative using the algorithm ACS.

In this proposal a comparison of the Global Pheromone is considered based on gradient of the image and based on CV of the image.

Image synthetic allow compare easily such the detection of contours using gradient and CV. The analysis of the results allows to conclude that the ACS algorithm based on GF-CV adapts and detects contours in a better way in an image with multiplicative noise.

It is proposed as future works:

- Perform tests on real images with ground of truth.
- Propose other detector of contours as GF and make the comparisons between is a new GF and already analysed.
- Extend the algorithm proposed for other types of noises like for example the noise Salt and Pepper.

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