



## Image Edge Detection with Fuzzy Ant Colony Optimization Algorithm

Z. Dorrani, H. Farsi\*, S. Mohamadzadeh

Department of Electrical and Computer Engineering, University of Birjand, Birjand, Iran

### PAPER INFO

#### Paper history:

Received 05 July 2020

Received in revised form 20 August 2020

Accepted 03 September 2020

#### Keywords:

Ant Colony Optimization Algorithm

Edge Detection

Fuzzy System

### ABSTRACT

Searching and optimizing by using collective intelligence are known as highly efficient methods that can be used to solve complex engineering problems. Ant colony optimization algorithm (ACO) is based on collective intelligence inspired by ants' behavior in finding the best path in search of food. In this paper, the ACO algorithm is used for image edge detection. A fuzzy-based system is proposed to increase the dynamics and speed of the proposed method. This system controls the amount of pheromone and distance. Thus, instead of considering constant values for the parameters of the algorithm, variable values are used to make the search space more accurate and reasonable. The fuzzy ant colony optimization algorithm is applied on several images to illustrate the performance of the proposed algorithm. The obtained results show better quality in extracting edge pixels by the proposed method compared to several image edge detection methods. The improvement of the proposed method is shown quantitatively by the investigation of the time and entropy of conventional methods and previous works. Also, the robustness of the proposed method is demonstrated against additive noise.

doi: 10.5829/ije.2020.33.12c.05

## 1. INTRODUCTION

Image edges are one of the simplest but most important elements in image processing. Therefore, the appropriate implementation of some image processing algorithms depends on the accuracy of edge extraction [1, 2]. The location of an object in an image can be measured by identifying its edges [3, 4]. Also, edge detection is one of the basic techniques in segmentation, separation, and understanding the position of targets in image and scene variation detection [5]. Edge detection is known as a critical tool in machine vision [6], separating the background in image compression in order to reduce computation time and storage.

There are many methods for extracting and detecting edges that differ in finding accurate edges [7]. A powerful operator such as the Canny operator [8] which is one of the most important tools in edge detection, may have problems with detecting disrupting edges.

The ACO algorithm is used to discover image edges. In the proposed method, the ACO algorithm with a fuzzy system is applied for image detection. In addition, the

following steps are applied in the multi-dimensional approach to obtain accurate edges: A) the connection provides a good quality in terms of connectivity and interconnection of the edges. B) Connecting to neighboring points can be considered quadruple or octahedral, resulting in two outcomes, C) the other parameters of the proposed algorithm are selected to provide better results.

In this article, the first steps of implementing an ACO algorithm are described based on how to find the edges. A fuzzy system is used in the proposed method and then the obtained results are presented. Finally, a summary of the results is presented and discussed.

## 2. RELATED WORKS

Several edge detection methods have been proposed to discover edges with first- and second-order derivative so far. The Canny edge detection algorithm is known as an optimal edge detector [8]. The globalized probability of boundary (gPb) algorithm combines contour detection and spectral clustering technique [9].

\*Corresponding Author Institutional Email: [hfarsi@birjand.ac.ir](mailto:hfarsi@birjand.ac.ir)  
(H. Farsi)

There are many methods for edge detection with ACO [10]. An algorithm based on the ACO is proposed for edge detection in the construction step and a repair operator in the improvement step. The hybrid ACO algorithm for edge detection is proposed by using heuristic and knowledge data in the manufacturing phase and a repair operator in the improvement phase [11]. In another method, the adaptive threshold value is defined based on particle swarm optimization to overcome the restraint of existing ACO-based edge detection techniques [12]. The feature selection is permitted by the ACO algorithm to determine the most protuberant and final features [13]. In [14], the reported method involved pre-processing, achieving the edges in an independent style, and emerging an algorithm to discover the best applicants of initial locations for the ant colonies.

The threshold-based techniques for edge detection with ACO are combined to use in an optical character recognition system [15]. This method is used to sharpen the edge shape of skin lesion images [16]. The reported method in [17] identified the complex area of the cover image and detected complex areas' pixels by using employed data in the ACO based information hiding method. The fuzzy logic is another method that simply answers the problems where static values cannot be obtained. Anwar and Raj proposed the adaptive-neuro fuzzy inference system for edge detection [18]. A bio-inspired edge detection method was suggested using a mixture of bird swarm algorithm (BSA) and fuzzy reasoning [19, 20].

To further develop edge detection methods, we have proposed an optimization algorithm for edge detection. In this approach, an ant's behavior of exploring optimal paths by using fuzzy rules is investigated. Ant colony optimization is used to identify edges of a ship in ocean water. To reduce time and complexity, the fuzzy function is used. The results of the proposed method confirm the clear edges of small and partial objects. The proposed method provides better results compared to other methods for edge detection.

### 3. PROPOSED METHOD

#### 3.1. Introducing ACO Algorithm

The aim of optimizing the ant colony is to find the best solution for a problem. In the natural world, ants are randomly searching for food. When they return to the nest, they leave a trail of pheromones if they find food. Other ants follow paths where pheromone levels are higher, return to the nest if food is found, leave another trace of pheromone behind, and the pheromone of that path is strengthened. As the ant travels shorter paths at a specific time, each path is better reinforced. The chemical structure of pheromone causes it to evaporate over time, thus reducing the amount of pheromone on less traveled paths over time.

In the algorithm inspired by the natural behavior of ants, the pheromone value of all points in the sample space of the problem is represented by a pheromone matrix. The path leading to the target consists of a set of points that have the highest values in the pheromone matrix. The algorithm starts by considering the initial pheromone values for each pixel and then updates the pheromone matrix based on the problem's information. When the pheromone value changes in successive steps of the algorithm are negligible, the algorithm is stopped and the path with the highest pheromone residue is considered as the best way to solve the problem.

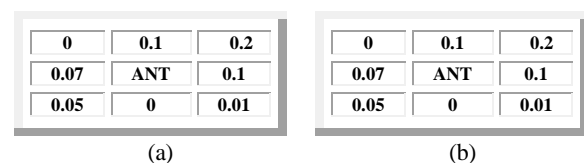
#### 3.2. ACO Method for Edge Detection

In this approach, a number of ants move on a two-dimensional image, hypothetically. An image edge is equivalent to the food which ants seek. First, the algorithm assigns a pheromone matrix to all pixels of the image so that the initial value of each component in the matrix represents the probability of each pixel being edged. This value is the same for all pixels. Then by applying the algorithm and using the equations of probability, the pheromone matrix value is changed and points where brightness level changes occur become more probable. When the ant lies on one pixel, the pheromone level of the pixel increases. At this time no other ants can be placed on this pixel. In other words, two or more ants cannot sit on one pixel at the same time. The next track of ant movement is chosen from 4 or 8 neighboring pixels. If it is assumed that an octagonal connection is used, the ant will choose from the 8 pixels in its vicinity the most probable pixel, and if two or more pixels have the same probability value, a pixel is randomly selected. In quadruple connection, the same previous steps are repeated, except that the next path has to be selected from four neighboring pixels.

Figure 1 shows the direction of the ant's movement at the octagonal and quadratic junctions. Therefore, the points with the highest probability in the pheromone matrix are separated as image edges. The steps for implementing the algorithm are described as follows:

**-Initialization step:** In the first pheromone matrix, the initial value of each component is  $\rho_{init} = 0.0001$ .

**-Construction step:** One of the ants is randomly selected from the X stage and is moved over the image to the Y stage. This ant moves with the probability obtained by the following relation [1] from a pixel to the neighboring pixel.



**Figure 1.** (a) Ant's movement path at the octagonal junctions (b) Ant's movement path at the quadratic junctions

$$P_{i,j}^{(n)} = \frac{(\rho_{i,j}^{(n-1)})^\alpha (\mu_{i,j})^\beta}{\sum_{l \in \delta_k} (\rho_{i,l}^{(n-1)})^\alpha (\mu_{i,l})^\beta} \quad (1)$$

where,  $P^{(n)}$ ,  $\rho^{(n-1)}$  and  $\mu$  are the probability of transfer, the pheromone value and the distance of motion from pixel  $i$  to pixel  $j$ . The values of  $\alpha$  and  $\beta$  are the pheromone impact and heuristic information, respectively. The pheromone matrix is updated twice during the execution of the algorithm, once after each ant moves using the following equation [1], and again when the search and completion of all ants is completed.

$$\rho^{(n)} = (1 - \lambda)\rho_{i,j}^{(n-1)} + \lambda\rho_{init} \quad (2)$$

where  $\lambda$  is the evaporation ratio,  $\rho_{i,j}^{(n-1)}$  is the Pheromone amount before the update step.

**Update step:** Once every ant has completed it's search, the pheromone matrix is updated using Equation (3) [1].

$$\rho^{(n)} = (1 - \omega)\rho^{(n-1)} + \omega \sum_{k=1}^k \Delta\rho^{(k)} \quad (3)$$

where  $\omega$  is the pheromone reduction coefficient and  $\Delta\rho^{(k)}$  is determined according to the following [1,20]:

$$\begin{cases} \frac{1}{L_k} & \text{if the } k\text{th ant goes from } i \text{ to } j \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

The edges of the image can be detected using the ant-optimization algorithm. All optimization algorithms contain hyperparameters. The values of these parameters are determined by either using the same values used by the algorithm's publishers, or investigated by researchers themselves through trial and error. Depending on the static parameters, the algorithm may be disorganized on some iterations. Therefore, standard ACO may in some iterations interfere with finding optimal edge points. In these cases, a fuzzy controller can solve this problem. Therefore, we use a fuzzy method to control the effect of pheromone and heuristic information.

**3. 3. Design of a Fuzzy System for Controlling ACO Parameters**

The amount of pheromone impact and heuristic information are influential parameters in the implementation of the algorithm so that increasing the pheromone effect strengthens the exploration ability and, if considered smaller, enhances the browsing ability. The heuristic information parameter is the opposite of the pheromone effect parameter, which means that it increases the pheromone linkage between the ants and reduces its browsing.

The first step in the design of a fuzzy system is to select the appropriate inputs and outputs according to the problem's conditions. Due to the problem's conditions and the requirement of uniform convergence for this algorithm, the fuzzy structure consists of two inputs and two outputs for parametric control of the convergence of this algorithm. The inputs to this system include the value of the objective function's fit and the number of

iterations. The two outputs are controlled by this fuzzy system, which is the effect of pheromone and exploratory information. The general approach of the proposed fuzzy system for controlling the parameters of the ACO algorithm is shown in Figure 2.

**3. 4. Membership Functions**

The fuzzy membership functions are defined according to the problem's conditions and their correct definition is required to provide an appropriate answer to the problem.

There is a great variety of membership functions. Choosing effective and rational rules for controlling parameters results in better performance. In this case, the trapezoid type is selected. The overlap conditions of the fuzzy system rules and decision levels shown in Figure 3 illustrate the effective and appropriate selection of membership functions.

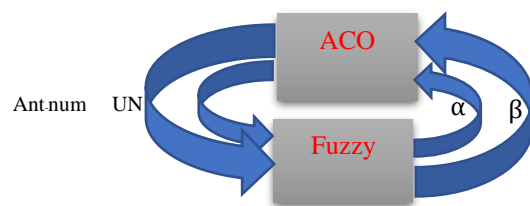
The rules for controlling input and output can affect global and local search, speed of response, and result in fewer steps being repeated, causing a reduce in response time, especially for immediate applications. So searches in the early stages of the nation (?) and as we approach the final stages of repetition, local search is saturated and more exploration is done.

**4. EXPERIMENTAL RESULTS**

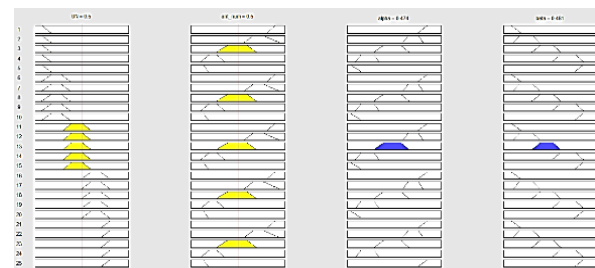
**4. 1. Standard Images**

Initially, the standard image is called with any size that is a factor of 8, and the ACO algorithm is executed on it. To run the algorithm, we need the basic parameters:

$$\alpha = 0.0001, \beta = 1, \lambda = 10, \omega = 0.6.$$



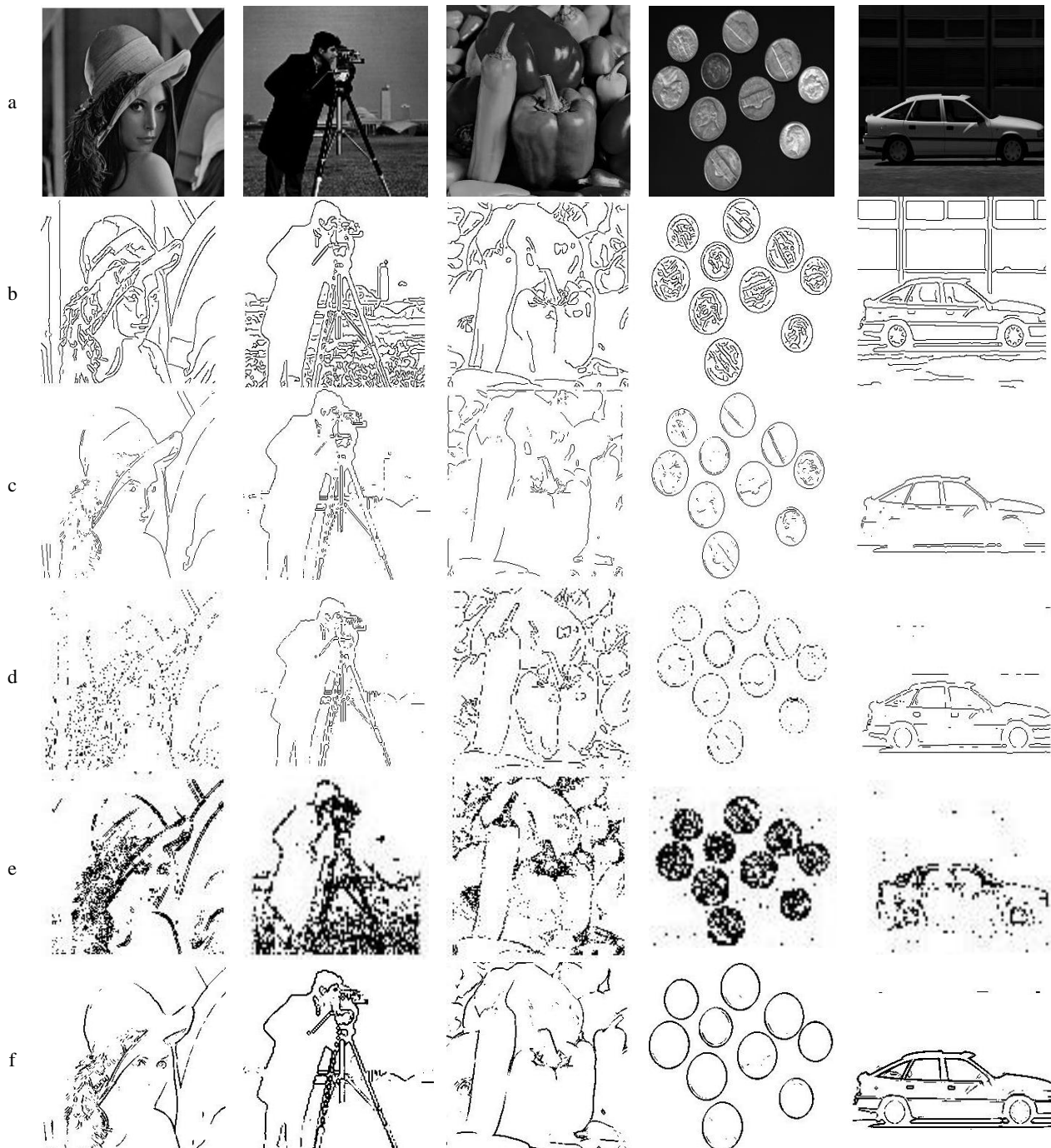
**Figure 2.** Fuzzy system for controlling the parameters of the ACO algorithm



**Figure 3.** Schematic of the fuzzy rules for fuzzy systems

The number of ants is 4 and each ant moves about 20 times during the construction phase. To run the algorithm, we selected some images and implemented the fuzzy ACO algorithm on them. To compare the proposed algorithm's performance at edge detection with robust edge detection methods such as Canny, Sobel, ACO edge detection, and Laplacian of Gaussian (LOG)

method [1], the simulation results are also shown in Figure 4. The proposed algorithm has demonstrated its ability to correctly identify the edges of the image. In any form it can be observed that the pixels of the edge are correctly recognized and compared to other edge detection methods, the sublimation and priority of the edge quality (?) are higher.



**Figure 4.** (a) Original image; (b) Detected edges using Canny method; (c) Detected edges using Sobel method; (d) Detected edges using ACO method; (e) Detected edges using LOG method; (f) Detected edges using the proposed method

To compare system and output performance, Shannon's entropy function is used [21]. The information that the output image holds can be measured by this function. The information in the image decreases as the value of entropy increases. This is calculated by:

$$H(I) = -\sum_{i=0}^L q_i \log q_i \quad (5)$$

where  $I$  and  $q_i$  are the image and the pixels' frequency having intensity  $i$ , respectively.

Table 1 shows the entropy values for the outputs of different edge detectors on various images. A higher value of entropy corresponds to more randomness and less information. The proposed algorithm achieves the least entropy value and is capable of discovering important edges.

Table 2 shows time values obtained by hybrid ACO, gPb and the proposed method over four standard images (Lena, Cameraman, Pepper and, Mandril). As observed, the proposed method's performance is better compared to hybrid ACO, and gPb.

**4. 2. Berkley Segmentation Dataset** To evaluate the effectiveness of the proposed method, images from Berkeley Segmentation Dataset have been used. Table 3 presents the entropy values for outputs of some of the edge detectors [19]. As observed, the proposed algorithm provides the minimum value.

**4. 3. The Medical Images** At this stage, the medical images are considered. Three skin lesion images [16, 22] are used (Figure 5).

The efficiency of the proposed method is tested by comparing the entropy of Canny and Prewitt operator in Table 4.

**4. 4. Noisy Images** To study the stability of the proposed method, Gaussian Noise is added to the images. As an example Figure 6 shows the results obtained by the proposed method.

**TABLE 1.** Entropy values for the outputs of different edge detectors on standard images

Image	Fuzzy BFO	Neuro-Fuzzy	BSA-Fuzzy	Proposed Method
Lena	0.5773	0.6997	0.5002	<b>0.3750</b>
Cameraman	0.6556	0.6135	0.6112	<b>0.4072</b>
Monarch	0.6929	0.7822	0.6772	<b>0.5452</b>
Barbara	0.6001	0.5667	0.5474	<b>0.3101</b>
Pepper	0.5662	0.5998	0.5453	<b>0.3837</b>

**TABLE 2.** Time values(s) for the outputs of different edge detectors on standard images with 256 \*256

Image	Hybrid ACO	gPb	Proposed Method
Lena	4.4	219.5	<b>3.33</b>
Cameraman	4.7	196.7	<b>4.366</b>
Pepper	4.1	227.1	<b>3.79</b>
Mandril	5.2	215.7	<b>4.9</b>

**TABLE 3.** The entropy values for the outputs of some of the edge detectors on Berkley segmentation dataset

Image	GA	PSO	ACO	Deep Learnig	BFA	Fuzzy+BFO	Neuro-Fuzzy	PSO for Noisy	BSA-Fuzzy	Proposed Method
35010	0.8211	0.7213	0.7715	0.6882	1.6124	0.6331	0.6110	0.6995	0.6002	<b>0.5960</b>
42049	0.8322	0.6811	0.7722	0.6243	1.5216	0.5999	0.6561	0.6778	0.5991	<b>0.3911</b>
118035	0.8836	0.6992	0.7765	0.6836	1.4245	0.5876	0.5788	0.6476	0.5521	<b>0.3980</b>
135069	0.9214	0.8112	0.8833	0.7210	1.2124	0.6675	0.6689	0.7889	0.6433	<b>0.4217</b>
119082	0.9914	0.8365	0.8987	0.7991	1.4642	0.7999	0.7989	0.8999	0.7782	<b>0.5711</b>



**Figure 5.** The medical images (skin lesion)

**TABLE 4.** Entropy values for the medical images

Image	Canny	Prewitt	Proposed Method
A	0.4791	0.1283	<b>0.1106</b>
B	0.7677	0.2174	<b>0.1293</b>
C	0.6238	0.1502	<b>0.0876</b>

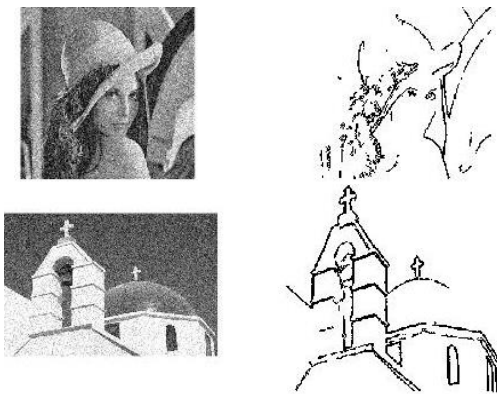


Figure 6. The proposed edge detection on noisy images

## 5. CONCLUSIONS

In this paper, an ACO algorithm was developed for edge detection. The fuzzy controller was used to control the algorithm's hyperparameters. The obtained results demonstrate the success of this algorithm in finding the edges of an image. The efficient and appropriate selection of fuzzy controllers as well as the membership functions can improve the convergence speed of the algorithm by preventing pheromone control as well as preventing the inertia and immobility of the ant during the algorithm implementation. This process results in a dynamic search corresponding to a finer edge. Using fuzzy abilities, we were able to improve the capabilities of the ACO algorithm. On the other hand, by fuzzing, we are able to improve the behavior of the algorithm against the anomalous position of some ants. Therefore, a smarter and more accurate algorithm resulted in increased edge search quality. The effectiveness of the fuzzy ACO based approach has been examined on images and the obtained results showed that the detected edges are more connected and smooth compared to other latest edge detectors while reducing time and entropy.

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### Persian Abstract

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#### چکیده

جستجو و بهینه‌سازی با استفاده از هوش جمعی روش‌هایی بسیار کارآمدی هستند که می‌تواند برای حل مشکلات پیچیده مهندسی مورد استفاده قرار گیرند. الگوریتم بهینه‌سازی کلونی مورچه مبتنی بر هوش جمعی است که از رفتار مورچه‌ها در یافتن بهترین مسیر در هنگام جستجوی غذا الهام گرفته شده است. در این مقاله از الگوریتم ACO برای تصویر تشخیص لبه استفاده شد. الگوریتم سیستم فازی برای افزایش پویایی و سرعت این الگوریتم پیشنهاد شد. این سیستم میزان فرومون و فاصله را کنترل می‌کند. بنابراین به جای یک مقدار ثابت برای پارامترهای الگوریتم، از مقادیر متغیر استفاده می‌شود تا فضای جستجو دقیق‌تر و منطقی‌تر شود. الگوریتم بهینه‌سازی کلونی مورچه فازی شده روی چندین تصویر پیاده‌سازی و عملکرد الگوریتم پیشنهادی نشان داده شد. نتایج نشان داد که این الگوریتم در استخراج پیکسل‌های لبه، کیفیت بهتری نسبت به روش‌های دیگر تشخیص لبه دارد که منجر به کاهش زمان و آنتروپی می‌شود. بهبود این روش از نظر کمی با بررسی زمان و آنتروپی در مقایسه با روش‌های متداول و کارهای قبلی نشان داده شده است. همچنین نشان دادیم که این روش در برابر نویز از پایداری خوبی برخوردار است.

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