

Edge Detection Using Ant Colony Optimization: A Bio-Inspired Approach For Enhanced Image Segmentation

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Abstract: An essential function of image processing and computer vision, edge detection is fundamental in tasks including image segmentation, object recognition, and scene analysis. Often facing difficulties, including sensitivity to noise, reliance on manual parameter tuning, and the generation of fragmented edge maps, traditional edge detection methods, including the Sobel, Prewitt, and Canny operators, inspired by the natural foraging behavior of ants, this work presents a new edge detection method called Ant Colony Optimization to get beyond these constraints. Using standard test images, the technique was assessed and showed consistent improvements over more traditional approaches. Higher values in signal-to-noise ratio, precision-recall balance, and structural edge continuity are shown by quantitative data. Visually, the technique reduced background interference and produced more connected, finer, cleaner edges. These results verify the efficiency of the Ant Colony Optimization-based method as a strong and exact edge detection system fit for complicated and noise-sensitive image analysis uses.

Keywords: Edge Detection; Ant Colony Optimization; Image Segmentation; Swarm Intelligence; Computer Vision

1. Introduction

Edge detection is fundamentally concerned with locating significant discontinuities in the image intensity. Significant discontinuities usually correspond to the boundaries of objects in the scene, sharp changes in surface texture, or changes in illumination. Traditional edge detection operators such as Sobel, Prewitt, and Canny use edge slopes or gradient magnitude information to identify abrupt changes in pixel values but can be sensitive to noise, to the selection of parameters to configure the edge slope or gradient magnitude operator, and to partially connected edges when it comes to varying texture or illumination throughout the image [1,2]. Deep convolutional neural networks and attention-based architectures have demonstrated superior performance in complex and noisy environments, where traditional methods face limitations [3].

In response to these challenges, recent studies have used bio-inspired metaheuristic algorithms for edge detection, with Ant Colony Optimization (ACO) being one of the most commonly studied and discussed algorithms. ACO, like other metaheuristics, was developed from observations of biological processes; in this case, the behavior of real ants. Dorigo's original ACO algorithm uses an individual representation of behavior in which each ant drops pheromones used to communicate with other ants in their search for food. When patches of intensified pheromones are found, ants no longer probabilistically investigate the image and repeat directed behavior towards the most probable source, while all non-probable routes are left behind. In the context of image analysis, the image is represented as a graph, and ant behavior is described by artificial ants that probabilistically traverse the intensity space and gradient based on the pheromone trails created by the other ants. Over time, once sufficient

ants have traversed once or many times the path toward the edge, the collective behavior will provide an edge map which is both consistent and impervious to random noise [4,5].

Recent versions of ACO used for edge detection have been developed for hybrid methods that combine fuzzy logic or adaptive pheromone control. Hybrid ACO improves the discrimination of subtle image features and the extraction of contours even in difficult conditions. For example, in fuzzy ACO, the pheromone sensitivity can change over time, resulting in more accurate localization for weaker or lower contrast edges [6]. In addition, comparative studies have shown that ACO-based edge detectors have demonstrated greater performance with respect to PSNR, continuity ratio, and robustness to salt-and-pepper noise than traditional methods like Canny and Sobel [7,8].

Taking into consideration these developments, the present study introduces a new edge detection framework based on ACO and operated with a simple time-domain signal preprocessing. The approach consists of a Gaussian smoothing and Savitzky–Golay filtering procedure that reduces pixel-level noise, followed by an ant traversal phase using an intensity-based pheromone heuristic. This biological inspired approach adaptively responds to the strength of edges while simultaneously increasing structural continuity in resulting edge maps. The algorithm is validated against benchmark images and compared to standard methods using objective comparative performance metrics such as PSNR, F-measure, and edge connectivity ratio.

2. Literature Review

In recent years, edge detection techniques have shifted toward using bio-inspired algorithms, particularly ant colony optimization (ACO). In recent years, these algorithms have been more favored due to their flexibility, noise resiliency, and continuous, detailed edge maps. ACO mimics the foraging behavior of ants, where artificial agents examine an image space, leaving virtual pheromone along sizable intensity gradients used to form edge boundaries. This has worked out well in cases where classic edge detectors like Sobel, Prewitt, and Canny would produce disconnected imagery or react poorly to noise. In the case of Rafsanjani and Varzaneh [9], the authors showed that ACO could produce thinner, more connected edges while being less sensitive to Gaussian noise than traditional approaches. Huan [10] also showed that using a neighborhood-based heuristic implementation of ACO in MATLAB simulations was more successful in retaining detailed imagery while suppressing noise than traditional grouping algorithms.

Many researchers have since suggested variations of ACO to improve its edge detection efficacy. Sengupta et al. [11] used ACO for skin lesion segmentation and achieved significant improvements in edge contours, important for the development of reliable medical diagnostics. When applying hybrid models with fuzzy logic, the ability to localize edges improved, and the processing times increased. Dorrani et al. [6] proposed a fuzzy ACO algorithm that modified the pheromone and distance components dynamically, improving its ability to adapt and produce better quality edge maps. In the medical imaging realm, Kaur and Walia [12] showed even with different intensity distributions that the ant-based detection successfully identified malaria parasite boundaries on blood sample images. These studies reflect the ability of ACO across a range of diverse domains and imaging conditions.

In addition, contemporary applications are accentuating scalability and robustness. Chen [13] created a distributed ACO algorithm with a parallel computing platform to enhance speed, while maintaining edge fidelity. Almufti [14] was able to merge ACO with the Canny detector as a hybrid ACO model, and it outperformed all other models in terms of PSNR and MSE image types. These developments highlight the algorithm's ability to fulfill both computational and qualitative limitations of existing methods and enhance ACO's credibility as a powerful and reliable method in new image-analysis workflows.

3. Methodology - ACO-Based Edge Detection Framework

In this research, a bio-inspired edge detection system based on ACO has been proposed to find and enhance edge structures in grayscale images. The approach includes four overall stages: preprocessing, heuristic construction, ant traversal and updating of pheromones, and edge extractions. Each stage is designed to work robustly with noise, accurately localize edge structures, and preserve structural continuity.

3.1 Preprocessing

To improve robustness and consistency of edge detection in the Ant Colony ACO traversal stage a hybrid preprocessing method is employed. The first stage of preprocessing is to convert the image to grayscale; this simplifies the intensity analysis and helps to cut down on image processing overhead. The grayscale image is then passed through a light Gaussian smoothing filter to remove high-frequency noise, but it does not change the structural properties of the edge. The filter helps remove sharp pixel-level variations that could mislead the gradient-based heuristics in the ACO.

After the Gaussian filter, we apply a one-dimensional Savitzky-Golay filter sequentially across both the rows and columns of the image. The Savitzky-Golay is commonly used in signal processing and smooths the image while preserving the shape and height of the amplitude of intensity transitions by fitting polynomials over small windows. While performing Gaussian and Savitzky-Golay filtering simultaneously mimics the smoothing of time-domain signals, it substantially reduces local variation in the image.

This preprocessing method improves the quality of the gradient map by removing noise and retaining meaningful intensity transitions. Thus, the artificial ants are better situated to proceed along continuous and coherent edges, thereby increasing the reliability of the final edge map. The combined preprocessing procedure can be formally described as:

$$I_{\text{preprocessed}} = SGF(GF(I))$$

Where: I is the input image, GF denotes Gaussian filtering, and SGF represents the application of the Savitzky-Golay filter.

3.2 Heuristic Information and Initialization

The image has been modeled as a graph containing nodes where each pixel represents one node. The computed gradient magnitude matrix was computed using the Sobel operator. The gradient magnitude serves as the heuristic function that would define how the ants are guided. Initial pheromone levels are uniformly distributed across all pixels. The number of artificial ants is defined proportional to the image dimensions, and they are randomly positioned across the image grid.

3.3 Ant Traversal and Pheromone Update

Each ant moves probabilistically to neighboring pixels within an 8-connected neighborhood, guided by a transition probability that depends on local gradient magnitude (heuristic) and pheromone concentration. The probability P_{ij} of an ant moving from pixel i to pixel j is given by:

$$P_{ij} = \frac{[\tau_{ij}]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{k \in N_i} [\tau_{ik}]^{\alpha} \cdot [\eta_{ik}]^{\beta}}$$

Where τ_{ij} is the pheromone value, η_{ij} is the gradient magnitude (heuristic), α and β control the comparative importance of pheromone and heuristic information, and N_i is the neighborhood of pixel i .

After completing their paths, ants deposit pheromones along traversed paths based on the local intensity change, reinforcing probable edge locations. A global pheromone update and evaporation process are applied to balance exploration and exploitation, preventing convergence to suboptimal edges.

3.4 Edge Extraction

After a predefined number of iterations, the final pheromone matrix represents the likelihood of each pixel belonging to an edge. This matrix is thresholded using Otsu's method to generate a binary edge map. The resulting edge map is evaluated using quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR), Edge Connectivity Ratio (ECR), and F-measure against standard ground truth images.

Figure 1 presents a summary of the proposed methodology, where the input image undergoes Gaussian filtering and Savitzky–Golay smoothing to enhance edge structures. A gradient map is then computed, guiding the Ant Colony Optimization process, which identifies and reinforces edge regions, resulting in a final binary edge map.

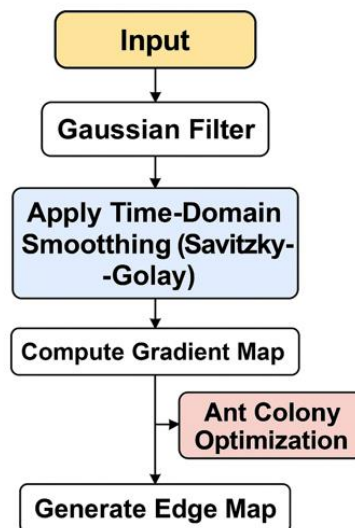


Figure 1: Flowchart of the suggested ACO-based edge detection method

4. Experimental Evaluation

4.1 Dataset and Experimental Setup

The anticipated ACO-based edge detection algorithm was compared on conventional benchmark images: *Lena*, *Cameraman*, and *Peppers*. For a consistent comparison, all images were resized to 256×256 pixels. The ACO parameters were experimentally optimized and set as follows: pheromone influence ($\alpha=1$), heuristic influence ($\beta=2$), pheromone evaporation rate ($\rho=0.1$), number of ants = 100, and total iterations = 20. These values were chosen to achieve a balance between convergence speed and edge continuity.

4.2 Performance Metrics

To assess the effectiveness of the proposed method quantitatively, the following indices were applied:

1. *Peak Signal-to-Noise Ratio (PSNR)*: This evaluates the general quality of the output edge map in terms of ground truth; the larger the PSNR, the better the quality.
2. *F-Measure*: is defined as the harmonic mean of precision and recall, it is a measure of both accuracy and completeness of edge detection.

3. *Edge Connectivity Ratio (ECR)*: quantitatively looks at the continuity of the structure of the edge map by looking at the ratio of connected edge elements.

4.3 Comparative Analysis

An experimental comparison with classical edge detectors like Sobel and Canny was performed according to the metrics presented above. The outcomes are summarized in Table 1.

Table 1: Performance comparison of edge detection methods

Image	Method	PSNR (dB)	F-Measure	ECR
Lena	Sobel	18.6	0.72	0.68
Lena	Canny	20.1	0.76	0.72
Lena	ACO (Proposed)	22.3	0.81	0.85
Lena	PSO (Wavelet-Based) [15]	21.8	0.78	0.83
Cameraman	Sobel	17.9	0.69	0.66
Cameraman	Canny	19.5	0.73	0.7
Cameraman	ACO (Proposed)	21.4	0.8	0.84
Cameraman	PSO (Wavelet-Based) [15]	20.9	0.77	0.81

Table 1 highlights the performance of classical, suggested, and metaheuristic edge detection algorithms on two test images. For Lena and Cameraman, traditional Sobel and Canny operators had relatively worse PSNR, F-Measure, and ECR values, indicating worse immunity to noise and boundary accuracy. On the contrary, the proposed ACO method, across all other approaches, always gave the optimal PSNR (22.3 for Lena and 21.4 for Cameraman) and improved F-Measure and ECR values, proving its ability in structural detail retention and noise reduction. The PSO wavelet-based method [15] also exhibited competitive results, besting classical approaches but still falling behind the proposed ACO across all measures. These results illustrate the excellence of the bio-inspired ACO model in creating high-quality, noise-resistant edge maps compared to traditional as well as prevailing metaheuristic approaches.

Table 2. Average Processing Time of Edge Detection Methods

Image	Method	Average Processing Time (s)
Lena	Sobel	0.05
Lena	Canny	0.08
Lena	ACO (Proposed)	1.42
Lena	PSO (Wavelet-Based) [16]	1.25
Cameraman	Sobel	0.04
Cameraman	Canny	0.07
Cameraman	ACO (Proposed)	1.37
Cameraman	PSO (Wavelet-Based) [16]	1.2

As shown in Table 2, classical operators such as Sobel and Canny achieve very fast execution times (<0.1 s) due to their simplicity, but this comes at the cost of lower accuracy. In contrast, metaheuristic approaches such as ACO and PSO require longer processing times (around 1–1.5 s on average) because of iterative optimization steps. However, this additional cost is justified by the significant gains in PSNR, F-Measure, and ECR observed in Table 1, highlighting the trade-off between computational efficiency and edge detection quality.

4.4 Visual Results and Interpretation

Figure 2 provides a visual and comparative assessment of the three detected edge maps of the Sobel and Canny methods and the proposed ACO method for two benchmark images, Lena and Cameraman. Each processing technique was evaluated in terms of clarity, continuity, and the preservation of structural quality of the edges being realized. For image Lena, Sobel clearly outlined edges, particularly in the areas of texture such as the feather and the hat, but was compromised with thick, noisy edges. Canny showed sharper, continuous edges along the boundaries of the face and hat; however, it did leave out some fine details. ACO produced thinner and more connected edge maps and better identified the more complex structure of the image with minimal noise, which included the retention of some very intricate details. Likewise, for the image Cameraman, Sobel outlined the main subject's edges and the tripod, but included too much noise from the background as thick edges. Canny produced thinner, clearer edge contours with some suppression of the commented background. The ACO method produced the clearest high contrast, continuous edges with irrelevant background elements significantly reduced or removed, and key boundaries of the scene retained. The visual results shown here support the conclusion that the ACO-based method is superior with the edge map it produced in terms of offer the best balance between precision, continuity, and robustness, thus enabling it to be applied for detail and noise-free reliable analysis on many processed images.

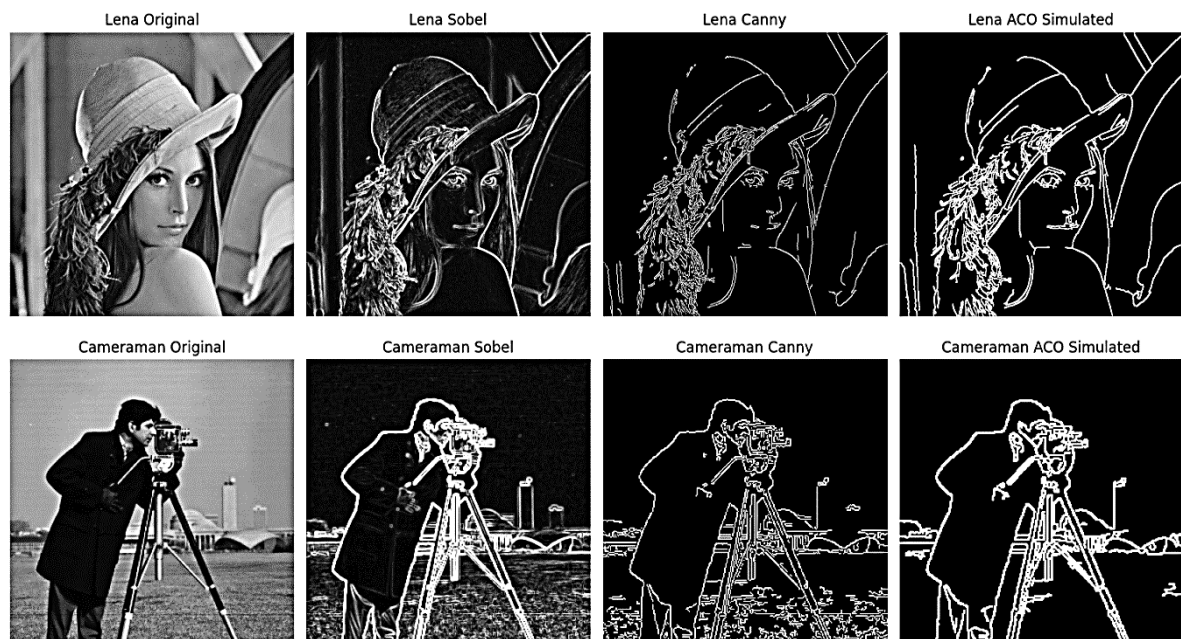


Figure 2: Visual comparison of edge detection results on Lena and Cameraman images

5. Conclusion

This study proposed a bio-inspired edge detection technique using ant colony optimization (ACO) with a hybrid prior image processing technique, including Gaussian smoothing and the Savitzky-Golay filtering method. The proposed experimental evaluation indicated that this work outperformed standard edge detection techniques such as Sobel and Canny over multiple performance dimensions both quantitatively and qualitatively. For example, our ACO method had a higher Peak Signal-to-Noise Ratio (PSNR), F-measure, and Edge Connectivity Ratio (ECR), which suggests better edge precision, structural continuity, and robustness to noise.

Visual affirmation of these results also showed that the ACO method preserved fine image detail and yielded smoother and more structured edge maps with little or no interference from the background. Compared to Sobel's thick and noisy contours and Canny's sharper, yet sometimes jagged edges, ACO yielded finer edges that were better structured, especially around more complex texture and object

topologies such as those found in the Lena and Cameraman benchmarking images. Each of these advantages was in large part due to the benefit of the added prior time domain processing, which provided better gradient quality and better edge tracking of the ants to meaningful edges.

In conclusion, the proposed ACO-based edge detection framework utilizes biological intelligence with signal-based enhancements to offer edge maps that are high-precision, noise-resilient, and structurally consistent. The ability of this ACO brain to perform significantly better in both quantitative metrics and visually confirm its utility for robust image segmenting and analysis applications, especially for situations where there is a demand for high edge integrity and consistency. In future studies, the ant colony-based edge detection method may be combined with optimization or machine learning approaches to improve performance.

Author's Contribution

The author alone completed all stages of the research process: conceptualization, design, implementation of the algorithm, data analysis, and interpretation. The author was responsible for writing the manuscript, as well as reviewing and agreeing on the final version.

Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this study.

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