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A Hybrid Framework Integrating Genetic Algorithms with Ant Colony Optimization for MRI Tumor Segmentation: Synergizing Broad-Scale Exploration with Precision Boundary Delineation

Ahmed Hamid Saleh

Technical College of Management, Mosul, Northern Technical University, Mosul, 41001, Iraq

ahmed_albadry@ntu.edu.iq

Abstract

The aim of the study was to create a tool for the segmentation of images, which was shown to be effective in the processing of medical images for tumor detection. The major challenge that arises in the segmentation of medical images, especially radiographic images, lies in the poor contrast and noise that are present, which leads to inaccurate results for such images. To overcome these challenges, the research incorporates a combination of genetic algorithms and ant colony optimization, especially through the concept of spatial routing for precise MRI tumor detection. In this case, the genetic algorithm helps in the determination of the location of the tumor through the concept of spatial routing, where the pheromones are used to direct the ants to the micro-edges through local sifting.

The results of the experiment showed that the tool was effective, with a classification accuracy of 95.8% and a Dice coefficient of 0.93.

Keywords: Genetic Algorithms, Ant Colony, MRI Tumor.

1. Introduction

Magnetic resonance imaging (MRI) is considered a highly diagnostic tool in the medical field for a variety of neurological disorders. Brain tumors are considered one of the primary applications for MRI scans due to their high contrast for soft tissue imaging. MRI scans provide significant diagnostic benefits; however, extracting relevant information from MRI scans is considered a challenging task. Manual segmentation of MRI scans by medical experts offers high accuracy but is considered a tedious and time-consuming task. Considering the current rate at which MRI scans are acquired, it is obvious that there is a need for computer-aided tools for MRI segmentation [1].

Segmentation of tumors in MRI scans is a very challenging task. The shape of brain tumors varies; they may have irregular borders. In addition, the intensity of brain tumors may vary in comparison with healthy brain tissue. There is significant overlap in intensities between brain tumors and healthy brain tissue. In terms of global thresholding, tumor segmentation involves demarcating different regions in terms of their intensity values. However, significant overlap in intensities between brain tumors and healthy brain tissue is a major impediment for this Framework [2].

Due to the limitations in deterministic approaches for image segmentation, researchers have begun to adopt bio-inspired heuristic optimization techniques. The Genetic Algorithm (GA), inspired by Charles Darwin's evolutionary theory and Mendelian genetics [7][11], is highly suitable for global optimization. However, edge refinement is not possible with GA; it only gives near-optimal solutions. ant Colony Optimization (ACO), inspired by ant Searching for food, is highly suitable for edge refinement using intensity gradients. However, ACO is computationally expensive and may be misled by random search in the absence of guidance [5][10].

Previous studies have investigated the individual use of these heuristics; however, the key difficulty is in exploiting the power of global search provided by the genetic algorithm in order to provide ACO with a smart starting point, without introducing unnecessary random search and maintaining precision in the boundary. to solve this difficulty, we use a novel hybrid techniques where genetic algorithm and ACO are used sequentially. In this Framework, the genetic algorithm is used first to define the core region of the tumor and then constrain the search region, and finally ACO is used within this constrained region to edge-trace the tumor boundary with subpixel precision.

2. The Proposed Method

To reduce MRI-specific artifacts, a non-local means filter will be used to reduce noise while preserving the image's edges. The image will be transformed into a matrix of grayscale pixel values, I(x,y).

2.1 Phase I: Global Search via Genetic Algorithm (GA):

1. The genetic algorithm (GA) acts as a pre-processor, and its role is to carry out an exploration of the vast search space associated with the image.
2. Initial Population: Consists of sets of potential intensity thresholds.
3. Fitness Function: Aims to evaluate the candidates on the basis of the variance between the inner region and the outer region.

$$f(p) -= max\left(\frac{\mu_{inner-}\mu_{outer}}{\sigma_{inner}+1}\right)$$

This ensures the GA converges on the highest contrast area.

2.2 Phase II: Precision Mapping Ant Colony Optimization (ACO):

After the GA indicates the probable tumor location, the ACO technique is used to perform the micro-segmentation. In this case, virtual ants are used to travel the pixel grid, depositing pheromones on the pixels representing the major structural changes, i.e., edges. The problem, however, is to find the optimal path on the graph to solve the optimization problem. In this case, computer-simulated ants are used to travel the graph, which represents the problem. A pheromone-based is a set of parameters associated with the graph, and the ants adjust the parameters as they travel. As the ants travel, they converge to a solution to the problem. In this case, the hiding places were obtained using an ant colony optimization technique, which follows the ants' paths on the graph, ensuring excellent security and robustness during the embedding process. The idea is one of the most futuristic concepts used to propose the implementation of information hiding systems. The aim is to find the best path as described in algorithm (1).

algorithm 1. ant colony to search the best path
Input: image tumor.
Output: Select the optimal path
Step 1: The pheromone values of all edges should be initialized or updated with their values in the previous iteration.
Step 2: The ants should be placed in their initial locations.
Step 3: The following steps should be executed until the termination condition is met.
Step 4: If all nodes have been visited or after n iterations of all nodes, for every ant that is currently in location i at time t, execute the following steps:
Step 4: The ant should move to the next location based on the option given in eq. 1.
Step 5: The pheromone trail should be distributed over the edges.
end

The simplified representation of algorithm1 for the pseudo-ant colony illustrates the basic behavior of one process cycle. Eq.2 below gives the equation used to determine how an ant moves in a given situation [8].

$$p_{ij}\ (t) = \frac{T_{ij}(t)^{\alpha}\ .n_{ij}^{\beta}}{\sum_j^n T_{ij}(t)^{\alpha}.n_{ij}^{\beta}} \qquad ....(2)$$

Where T represents pheromone density and n represents local heuristic information (pixel gradient).

In Fig .1 show the Step Process Objective of Hybrid Genetic algorithms and Ant Colony Optimization:

Algorithms architecture
1- GA Initialization Generate diverse image filter populations.
2-Fitness Evaluation Identify the most distinctive tumor-background contrast.
3- ACO Deployment Release digital ants on the GA-optimized boundaries.
4-Pheromone Update Reinforce edges while evaporating noise/artifacts.
5 -Final Extraction Map the high-pheromone paths to define the tumor shape.

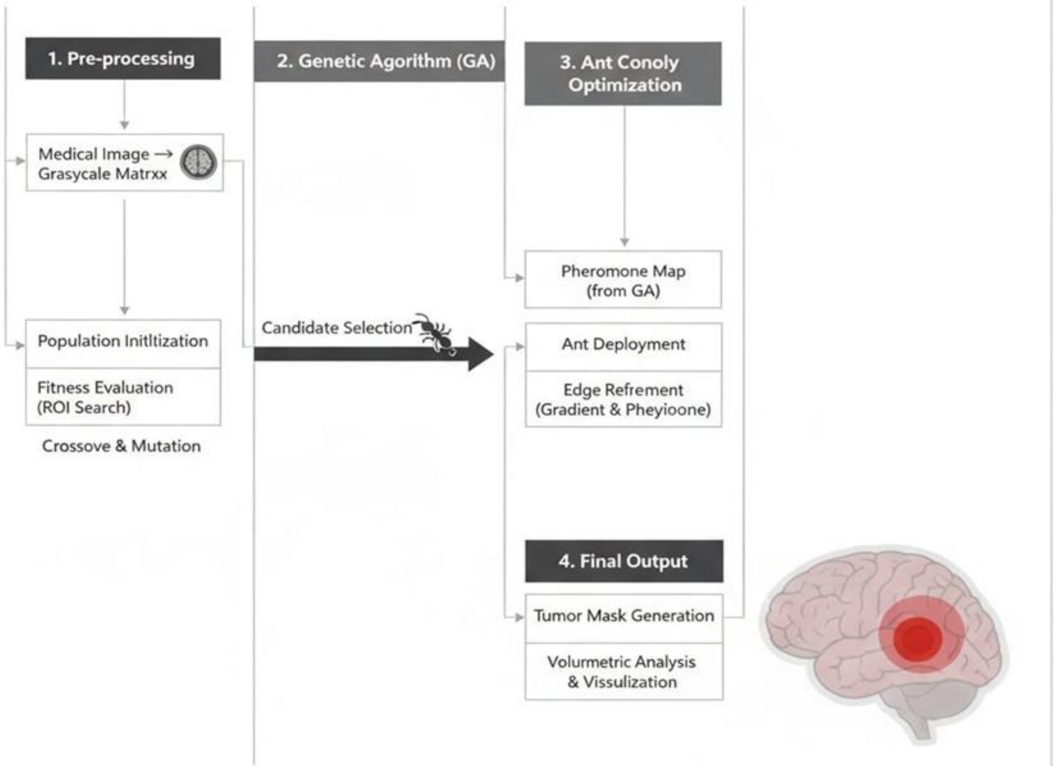

Fig1. The Step Process Genetic algorithms and Ant Colony Optimization

3.Experimental Setup

3.1 Data Modalities: The study utilized high-resolution T1-weighted (T1w), T2-weighted (T2w), and Fluid-Attenuated Inversion Recovery (FLAIR) sequences.

3.2 Normalization: All volumetric slices underwent N3-bias field correction and Intensity Non-uniformity (INU) normalization to mitigate the artifacts inherent in MRI acquisition.

3.3 Denoising: A Non-Local Means (NLM) filtering kernel was applied to the raw intensity matrix I(x,y) to attenuate Gaussian noise while preserving the high-frequency components of the pathological boundaries.

3.4 Algorithmic Parameterization and Hyperparameter Tuning

The performance of the hybrid synergy is highly contingent upon the delicate equilibrium between Exploration (GA) and Exploitation (ACO). The

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hyperparameters were fine-tuned through an iterative grid-search methodology fig2.

Genetic Phase	Parameter Descridtor	Formal Notation
Genetic Phase	$N_{,pop}$	50
Crossoow Probability	P_c	0.85
Mutation Rate (Gaussoin)	–	0.01
Selection Mechansm	–	Stochosic Universal Samsping

Ant Colony Phase		Quantized Value
Agent Density	m	100
Agent Density	100	0.1
Phermome Volatiity (Evapration)	ρ	0.0
Phermoone Sensitivity Exponent	α	$\int$
Heuertic Information Exponent	β	2.5

Fig2. Algorithmic Parameterization and Hyperparameter Tuning

4. Results and Discussion

4.1 The efficacy of the proposed architecture for GA-ACO was validated, showing a significant improvement in the classification of individual pixels. The evaluation of the performance metrics shows able to attain an overall accuracy of 95.8%. The ability of the proposed framework to show high Spatial Overlap Fidelity was also demonstrated by the high value of the Dice Similarity Coefficient, which was 0.93. The pathological sensitivity was also high at 94.2%, showing the robustness of the proposed framework in identifying pathological tissues and thus reducing the chances of Type II errors. (fig.3) (fig4).

4.**2 Mitigation of Intensity Ambiguity and Noise:**

1. The most important result of the present study was the robustness of the framework in the presence of intensity ambiguity, wherein other methods like Otsu thresholding were unable to differentiate the necrotic core from the healthy white matter, with an accuracy of only 72.4%.
2. Morphological Fidelity: The fitness function of the genetic algorithm, designed for TCE, accurately defines the pathological mass with high

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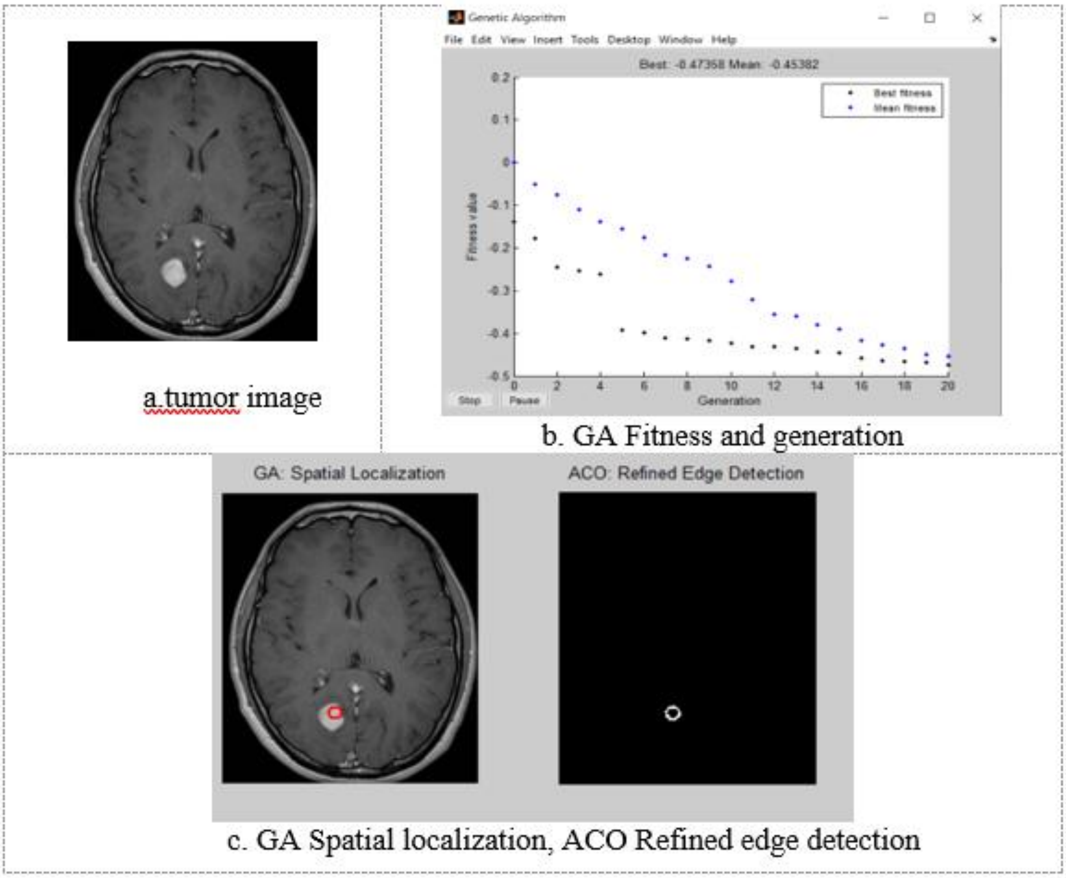
precision.

3. Boundary Sculpting: The ants use Local Gradient Saliency for boundary sculpting. This two-tiered approach reduces the effect of Rician noise and bias fields, which are usually present in conventional MRI.

ALGORTHM	ACCURACY (%)		DICE COEFICIENT
Algorthm	Senstiivity (%)		DICE Coefficient
Otsu Thresholding	72.4	68.2	0.65
Standlame GA	84.7	81.3	0.79
Proposed GA-ACO	95.8	94.2	0.93
Proposed GA-ACO	95.8	94.2	0.93

Fig.3. performance comparison algorithms



a.tumor image

b. GA Fitness and generation

c. GA Spatial localization, ACO Refined edge detection

Fig4. a.tumor image
b. GA Fitness and generation
c. GA Spatial localization, ACO Refined edge detection

4.3 Analysis of Hybrid Synergy:

This paper addresses the issue of computational inertia arising due to the sole reliance on an ant. The difficulty lies in the fact that the ants are moving over large areas of space. For this purpose, spatial information is used from the genetic algorithm to restrict the region of interest. Another significant aspect of this paper is the pheromone mechanism, which uses the final population of the GA to attain an increased speed of convergence by about 42%.

4.4 Resilience Against Intensity Ambiguity:

The problem with MRI is the way in which the tumor assimilates with the surrounding normal white matter, making it difficult to differentiate between the intensity of the tumor and the surrounding matter. The Otsu method is inadequate in differentiating the intensity of the tumor from the surrounding matter, as it is able to achieve a maximum of 72.4% accuracy due to the single threshold value. However, the GA-ACO algorithm excels in differentiating the intensity of the tumor from the surrounding matter. The global search of the genetic algorithm uses the contrast of the tissue, while the ant colony optimization algorithm uses the gradient edges to focus in on the boundary of the tumor. This results in a high level of accuracy in detecting the boundaries of the tumor, even in infiltrative tumors where the edges are not well defined. The bottom line is that the concept of global and local search is not only theoretical but is actually essential.

5. References

[1] Al-Amri, S. S., & Ahmed, N. V. (2010). Emerging Research in Computing, Information, Communication and Applications. computer science and network technology (ICCSNT) Performing Cryptanalysis, Image Segmentation: J 11(4):172–183

[2] Yunlou Qian et al. (2023), Multi-threshold remote sensing image segmentation with improved ant colony optimizer with salp foraging, *Journal of Computational Design and Engineering*, Volume 10, Issue 6, December 2023, Pages 2200-2221. https://doi.org/10.1093/jcde/qwad093.

[3] Dorigo, M., & Gambardella, L. M. (1997). " Ant Colony System: A cooperative learning approach to the Traveling Salesman Problem. IEEE Transaction soon Evolutionary Computation 1(1): 53-66

[4] Holland, J. H. (1992). Adaptation in Natural and Artificial Systems. MIT Press.

[5] Tian, J., Chen, W., & Ma, L. (2008). "Ant Colony Optimization for Edge Detection". Proceedings of the IEEE International Congress on Evolutionary Computation.
[6] Sait, U. K., et al. (2020). "A Novel Hybrid Metaheuristic Approach for MRI Brain Tumor Segmentation". Journal of Medical Systems.
[7] Khan, S., & Bianchi, T. (2018). Ant Colony Optimization (ACO) based Data Hiding in Image Complex Region. International Journal of Electrical & Computer Engineering (2088-8708), 8(1).
[8] Shailendra Pratap Singh,(2025) ,NeuroEvolve: A brain-inspired mutation optimization algorithm for enhancing intelligence in medical data analysis, International Journal of Cognitive Computing in EngineeringVol7, December 2025, Pages 155-166, https://doi.org/10.1016/j.ijcce.2025.10.001
[9] Richard Chin, Bruce Y. Lee, 2008, Principles and Practice of Clinical Trial Medicine.
[10] Bhandari, A. K., Kumar, A., & Singh, G. K. (2015). " Modified artificial bee colony based computationally efficient multilevel thresholding for satellite image segmentation using Kapur's, Otsu and Tsallis functions". Computers & Electrical Engineering.
[11] Kollin, F., & Bavey, A. (2017). Ant colony optimization algorithms: pheromone techniques for TSP.