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MODIFIED ANT COLONY OPTIMIZATION ALGORITHM FOR BRAIN MRI IMAGE SEGMENTATION AND BRAIN TUMOR DIAGNOSIS

Deepak A. Patil[1], Prof. S.N.Patil[2]

Department of Electronics Engg. P.V.P. Institute of Technology, Budhgaon, (India)

ABSTRACT

Brain tumor is uncontrolled growth of tissues in human brain. This tumor, when turns into cancer it becomes life threatening. So medical imaging is necessary to detect the exact location of tumor and its type. Medical imaging is a effective and easy diagnosing method for any disease. Brain image segmentation is a complex & challenging part in the medical image processing. MRI scan has become a particularly useful medical diagnostic tool for brain tumor cases. MRI provides detailed information about brain tumor anatomy, cell structure for effective diagnosis treatment. The imagse formed by MRI are in high tissue contrast and have less output. There are many metahuristic methods used for segmentation of brain MRI images. Ant Colony Optimization is a emerging segmentation technique used in brain image segmentation and brain tumor diagnosis.Ant colony optimization is a technique for optimization that was introduced in the early 1990's. The inspiring source of ant colony optimization is the foraging behavior of real ant colonies. The artificial ant colonies for search of approximate solutions have influenced from behavior of real ant colonies. Ant colony optimization algorithm is a probabilistic technique for solving computational problem inspired by foraging behavior of ants. In this paper there is an approach to modify ant colony algorithm efficiency. In this approach there is a balance between ants direction based on pheromone distribution.

Keywords: ACO, Brain Tumor, K-Means Clustering, Magnetic Resonance Imaging (MRI), Pheromone.

I. INTRODUCTION

The MR cerebrum picture division is an imperative and testing issue going up against grain mapping. In instance of neurodegenerative issue, for example, Alzheimer ailment, in developments issue, for example, Parkinson or Parkinson related disorder, in white matter metabolic or fiery sickness, in inherent cerebrum contortions or in post-traumatic disorder there are anomalous in dark and white matter volumes in mind likewise the programmed division of cerebrum MR pictures, in any case, remains a determined issue. Programmed and dependable tissue characterization is further entangled by the cover of MR forces of various tissue classes .Brain tumor is a gathering

of anomalous cells that becomes within the mind or around the cerebrum and spinal rope . Tumors have specifically demolished all solid cerebrum cells. Other mind tissues inside the skull are harmed by tumor additionally it gain the space inside the cerebrum and bringing about irritation, cerebrum swelling and weight inside the skull. X-ray utilizes a capable attractive field, radio Frequency beats and a PC to create nitty gritty pictures of organs, delicate tissues, bone and for all intents and purposes all other inside body structures. It doesn't utilize radiation X-beams and MRI gives point by point pictures of cerebrum and nerve tissues in various planes without hindrance of bones[4]. Insect state advancement (ACO) is a standout amongst the latest and productive systems for estimated improvement. The ACO calculations are propelled by genuine subterranean insect settlements. . All the more particularly, motivation behind ACO is by scrounging conduct of ants. Subterranean insect stores one of the synthetic called pheromone which is useful for backhanded correspondence between different ants in the settlement, which helps them to discover short ways between their home and sustenance sources.

This normal for genuine subterranean insect settlements is abused in ACO calculations with a specific end goal to tackle advancement issues. The advancement of these calculations was enlivened by the perception of insect states. Ants are social creepy crawlies. They live in provinces and their conduct is represented by the objective of state survival instead of being centered around the survival of people. The conduct that gave the motivation to ACO is the ants' scrounging conduct, and specifically, how ants can discover most brief ways between sustenance sources and their home [3]. At the point when looking for sustenance, ants at first investigate the range encompassing their home in an irregular way. While moving, ants leave a concoction pheromone trail on the ground. Ants can notice pheromone. While picking their direction, they have a tendency to pick, in likelihood, ways set apart by solid pheromone fixations. When a subterranean insect finds a sustenance source, it assesses the amount and the nature of the nourishment and conveys some of it back to the home. Amid the arrival trip, the amount of pheromone that a subterranean insect leaves on the ground may rely on upon the amount and nature of the nourishment. Ants Shortest way and longest way distinction is appeared by taking after figure

II. LITERATURE REVIEW

By Myung-Eun Lee et al proposed that process imagesegmentation, not only efficiently segments thetarget and the background, but also provides thesegments thin parts more effectively[1].Improved ant colony algorithm was done by improving tendency of ant to move in different direction in probabilistic selection rule. This algorithm shows balance between the ant’s direction and distribution of pheromone. The region detected as tumor is more distinct, clear and without any extra margin which is usually caused by inflammation [3]. The swarm intelligence approach for detection of brain tumor segmentation in MRI .It proposed ant colony optimization algorithm is possible to accurately segment the tumor portion from MRI.Swarm algorithm is based on behaviors of different swarm of animals and insects [4]. The algorithm which deals with technique ACO hybrid with fuzzy algorithm has proposed by Dr. M. Karnan in which Ant Colony Optimization. The tumor position and pixel similarity are measured with

Radiologist report. Only the pixel having optimum label are extracted from the original brain image to form segmentation image [7]. The merit of improved implementation of brain segmentation using meta heuristic algorithm is that automatic segmentation is detecting the required tumor tissues from brain MRI in two different approaches namely algorithmic and non algorithmic. The automatic segmentation of brain tumor from MRI described a gradient-based brain image segmentation using Ant Colony Optimization and block based technique [8]. Ant Colony Optimization to solve many optimization problems with good discretion, parallel, robustness and positive feedback proposed by Myung-Eun Lee. This algorithm not only give robust segmentation but also segment thin parts more effectively also this algorithm has advantage that effectively segment images [9].

A non-parametric distribution model including all statistical information of different parts of brain is made by simple healthy brain MRI Images and then it will called as optimization of cost function. Based on global rather than pixel wise information, the proposed algorithm does not required a complex learning from a large training set, as is the case in existingmethods [10].

Random Field with Parallel Ant Colony Optimization and Fuzzy C Means for MRI Brain Image segmentation investigated the most effective optimization method, known as Hybrid Parallel Ant Colony Optimization, new CAD system is developed for verification and comparison of brain tumor detection algorithm. This algorithm determines optimal threshold value by selecting initial cluster points the results are compared with existing approaches and find result faster than others [11]. Ant Colony Optimization is introduced for resolving for edge detection in biomedical images. Proposed method, uses artificial neural network with supervised learning along with momentumto improve edge detection based on ACO the proposed method compared with Jing Tian method and finds higher speed lees processing time the experimental result shows that make useto improve edge detection based on ACO the proposed method compared with Jing Tian method and finds higher speed lees processing time the experimental result shows that make useneural network are very effective in edge detection based on ACO [12].

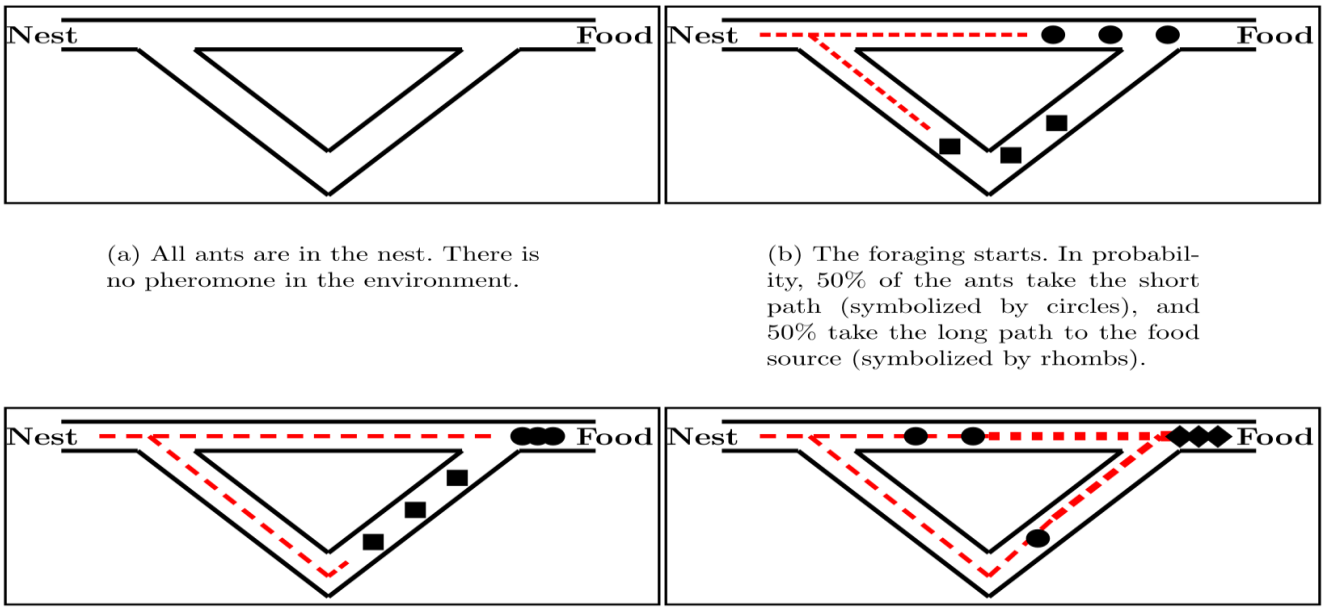
III.SEGMENTATION

At begin insect picked arbitrary way amongst home and sustenance source a large portion of the ants pick one or other of two branches. At starting stage ants have irregular options they select with a similar likelihood any of the branch. However, in light of arbitrary vacillations, a couple of more ants will choose one branch over the other. Since ants store pheromone while strolling, a bigger number of ants on a branch brings about a bigger measure of pheromone on that branch; this bigger measure of pheromone thusly invigorates more ants to pick that branch once more, thus on until at long last the ants unite to one single way.

Ants foraging for food follows the quality of volatile chemical substance that is pheromone and decide to follow the path with high probability and their by reinforce it with a further quantity of pheromone. The probability that an ant choose a path increases with the number of ants choosing the path increases with number of ants choosing the path at previous time and with the strength of pheromone concentration [3]. In order to solve the problem, ant k uses

probabilistic selection rule to choose a path, probability of kth ant movement from I to j can be calculated by equation.

$$P_{ij}^{k} = \frac{[\tau_{ij}]^{\alpha}[n_{ij}]^{\beta}}{\sum_{l \in N_i^k}[\tau_{il}]^{\alpha}[n_{il}]^{\beta}}, \text{if } j \in N_i^k$$



(a) All ants are in the nest. There is no pheromone in the environment.

(b) The foraging starts. In probability, 50% of the ants take the short path (symbolized by circles), and 50% take the long path to the food source (symbolized by rhombs).

(c) The ants that have taken the short path have arrived earlier at the food source. Therefore, when returning, the probability to take again the short path is higher.

(d) The pheromone trail on the short path receives, in probability, a stronger reinforcement, and the probability to take this path grows. Finally, due to the evaporation of the pheromone on the long path, the whole colony will, in probability, use the short path.

Where τ_{ij} is the amount of deposited pheromone between nodes *i* and *j* and also Ni^k is neighborhood nodes for ant *k* in the node*i*. Constants α and β will control the influence of pheromone and heuristic function. An ant will consider the target as a food source when the value of p exceeds a threshold. During the process of finding a food source, each ant has its own threshold λ. Then, the pheromone deposition τat pixel can be defined as[1].

$$\tau = \begin{cases} \eta & p < \lambda \\ \eta + p * u & p \geq \lambda \end{cases}$$

where η is a constant amount of pheromone; p is a constant weighting coefficient; u is the rate as interesting to the

ants searching for a food source. Therefore, with the ant moving, the pheromone amount on every path changes. Through one circulation, the pheromone amount on every path is adjusted.

$$T_{new} = (1-e)^{*}T_{old} + e^{*}T_{0}$$

At initial stage when there is no issue of mostly deposited pheromone ants move by any random path. So ant can move any of the eight direction .Ants random direction is given by the figurebelow[2].

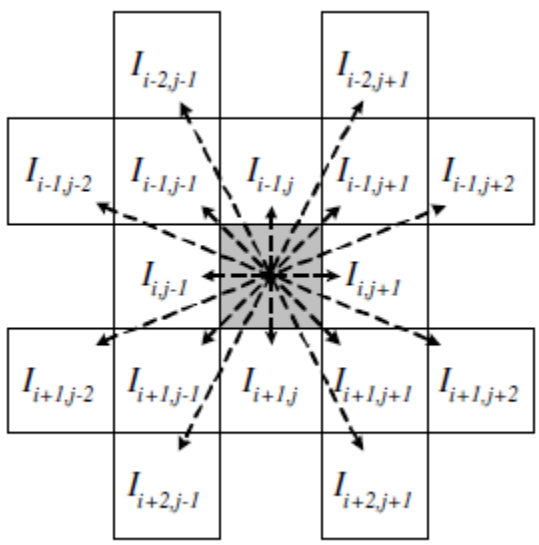


Fig. 1. A local configuration at the pixel position Ii,jfor computing thevariation Vc(Ii,j)

where Z =Vc(Ii,j), which is a normalization factor, Ii,j is the intensity value of the pixel at the position(I,j) of the image **I**, the function Vc(Ii,j) is afunction of a local group of pixels c (called the *clique*), and its value depends on the variation of image's intensity values on the clique c (as shown in Figure 1). More specifically, for the pixel Ii,j under consideration, the function Vc(Ii,j) is

$$Vc(I_{i,j}) = f\,(|I_{i-2,j-1} - I_{i+2,j+1}| + |I_{i-2,j+1} - I_{i+2,j-1}|$$
$$+|I_{i-1,j-2} - I_{i+1,j+2}| + |I_{i-1,j-1} - I_{i+1,j+1}|$$
$$+|I_{i-1,j} - I_{i+1,j}| + |I_{i-1,j+1} - I_{i-1,j-1}|$$
$$+|I_{i-1,j+2} - I_{i-1,j-2}| + |I_{i,j-1} - I_{i,j+1}|)\ .$$

To determine the function f(·) in (6), the following four function are considered they are mathematically expressed as follows

$f(x) = \lambda x$, for $x \geq 0$, (7)

$f(x) = \lambda x/2$, for $x \geq 0$, (8)

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$f(x) = \sin\pi x/2\lambda \quad 0 \le x \le \lambda;$

0 else.(9)

$f(x) = \pi x \sin(\pi x/\lambda)/\lambda \quad 0 \le x \le \lambda;$

0 else.(10)

IV.K-MEANS CLUSTERING

Clustering is a process for classifying objects or patterns in such a way that samples are more similar to one another. K-means is one of the simplestunsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early groupage is done. At this point we need to re-calculate k new centroids as barycenters of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the k centroids change their location step by step until no more changes are done. In other words centroids do not move any more.By normalizing pheromone matrix and primary image got the binary image. Then k-means clustering is applied to binary image which creates final segmented image.

The algorithm consists of following steps.

1. Place K points into the space represented by the objects that are being clustered. These points represent initial group centroids.
2. Assign each object to the group that has the closest centroid.
3. When all objects have been assigned, recalculate the positions of the K centroids.
4. Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated.

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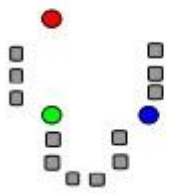


Figure 1 Initialization of K-Means

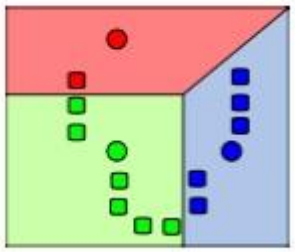


Figure 2 Generation of K clusters.

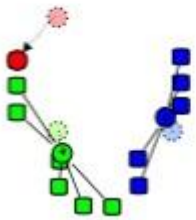


Figure 3 Generation of new K- mean.

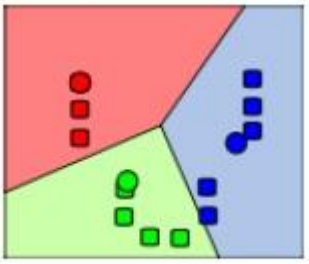
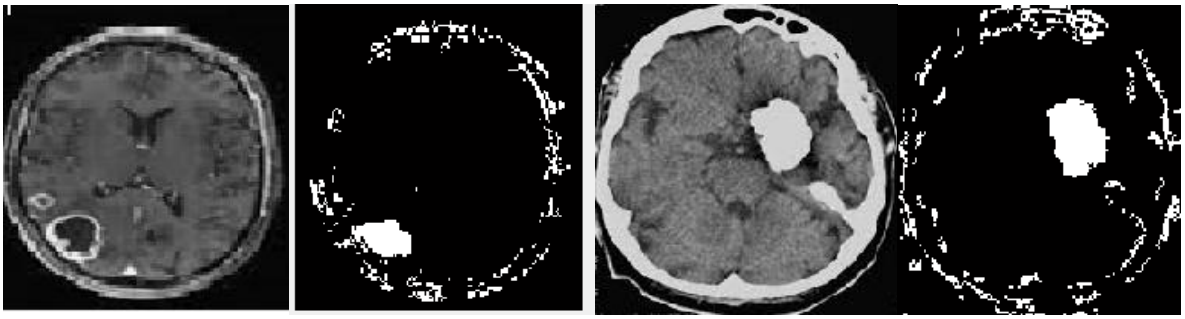


Figure 4 Convergence of the clusters.

V. RESULT

Time complexity of this algorithm depends on image size, number of algorithm iterations, number of ants and number of steps for each ant. In our implementation, the best run time was less than 1minutes, and the worst was about 2 minutes.Results of this algorithm are shown in Fig. below



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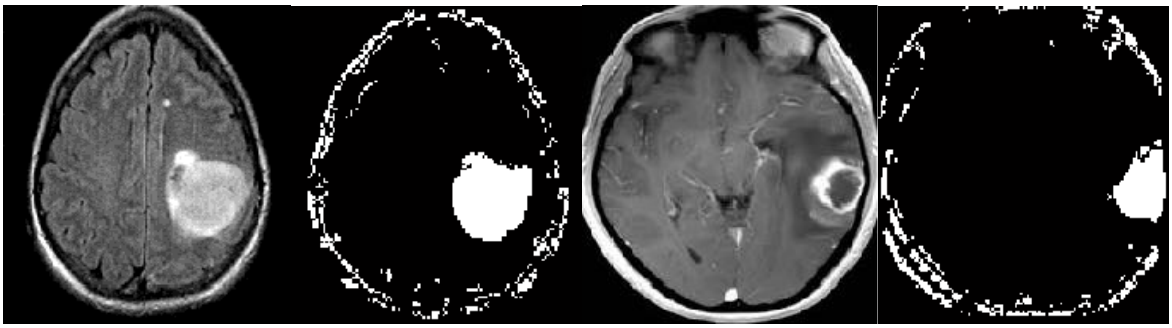

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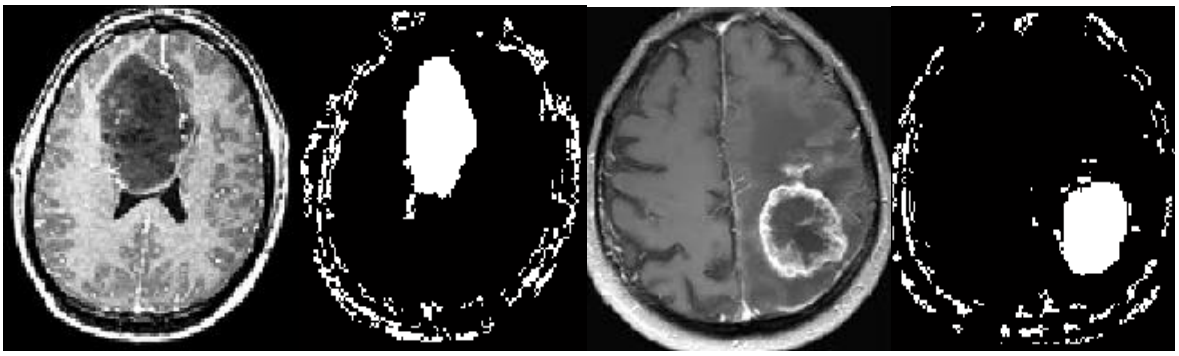

V V VI VI

Original Image Proposed algorithm Original Image Proposed algorithm

VI.CONCLUSION

Brain MR image segmentation is an important and challenging part and require more efficient algorithm. Ant colony optimization gives better edge detection comparison with traditional method. ACO follows the probabilistic rule for identification of tumor, so it gives easy and efficient output. In this paper we have reach to finding exact location of tumorand impact of tumor on tissues of brain. Also we have success to reduce computation time required segmentation less than 1 minute and high efficiency.

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