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MRI Brain Tumor Segmentation Using Improved ACO

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Abstract

Brain tumor segmentation consists of separating the different tumor tissues (solid or active tumor, edema, and necrosis) from normal brain tissues: gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF). In tumor studies, the existence of abnormal tissues may be easily detectable most of the time. However, Segmentation of these images is more difficult than natural images because their functional sensitivity is higher than other images. Ant-based clustering is a clustering algorithm that imitates the behavior of ants. In this algorithm, ant’s direction and its tendency to go to the next site is regarded for calculating the probability of choosing the next site by the ant. Furthermore, in calculating the probability of the ant's next move, a balance is made between the effect of the ant direction and the amount of pheromone distributed. Thus this algorithm is used for segmentation of brain images and diagnosing tumors. Experimental results show that this method is feasible, efficient and superior to other clustering techniques such as K-means and FCM.

Keywords: Segmentation, brain MRI, ACO , pheromone, K-means, Fuzzy C-means.

1. Introduction

Segmentation subdivides an image into its regions of components or objects.It is an important tool in medical image applications such as radiotherapy planning, clinical diagnosis. As an initial step segmentation can be used for visualization and compression. The task of image segmentation is to divide an image into a number of non-overlapping regions, which have same characteristics such as gray level, color, tone, texture, etc [1]. A lot of clustering-based methods are available for image segmentation in medical imaging.

Segmentation of the brain structure from magnetic resonance imaging (MRI) has received paramount importance as it is vital for feature extraction, image measurements and image display. It can be applied in the volumetric analysis of brain tissues such as multiple sclerosis, epilepsy, Parkinson’s disease, Alzheimer’s disease, cerebral atrophy[2].

Tumor is an abnormal growth of cells or in a word the "cancer". Generally, brain tumors have various shapes and sizes which are different from one case to another, and they do not follow any particular pattern. In the past few decades, although numerous methods have been introduced, MR images are still very difficult to interpret. One major goal in tumor imaging research is to accurately locate the cancer. This paper deals with the implementation of improved ACO Algorithm for detection of tumor in brain MR images. Ant colony optimization is a cooperative search algorithm inspired by the behavior of real ants.

Numerous methods are available for MRI images segmentation and tumor detection. Two commonly used clustering algorithms are the K-means, the fuzzy C-means algorithm. The K-means clustering algorithm clusters data by iteratively computing a mean intensity for each class and segmenting the image by classifying each pixel in the class with the closest mean. It is used because it is simple and has relatively low computational complexity.

Fuzzy c-means (FCM) algorithm is one of the most widely used fuzzy clustering algorithms in image segmentation. FCM algorithm was first introduced by Dunn and later extended by Bezdek. Unlike k-means clustering which force pixels to belong exclusively to one class, FCM allows pixels to belong to multiple clusters with varying degrees of membership.

2. ANT Colony Algorithm

The ant colony optimization algorithm (ACO) was proposed in 1997 for the first time as a multi-agent method for solving optimization problems such as the traveling salesman problem by Dorigo and Gambardell[3]. Ant colony optimization (ACO) is an evolution simulation algorithm. The study illustrates that ants are social insects which live in colonies, and tend to survive the colony rather than surviving individuals.

The amazing characteristic of ants is their behavior in the process of searching for their food. Moreover, they search by finding the shortest path between the food source and their nest. This behavior is a kind of mass intelligence, in which elements demonstrate a random behavior. It is an indirect mode of communication in which ants being distant from each other tries to contact with each other through producing and reacting with the stimuli. In this way they deposit a chemical like substance called pheromone on the ground while foraging for food. Ants’ movement is based on a simple instinctive behavior. They choose the path which has more pheromone or in other words, an ant tracks the path that the most other ants have passed through, and assumes that this most traveled path has the best source of food. This simple scheme is an effective mechanism for finding the optimal solution or best path selection.

Artificial ants are used in ACO to travel in the graph to search for optimal paths according to the pheromone information. The pheromone on each edge is evaporated at a certain rate at each iteration. It is also updated according to the quality of the paths containing this edge.

3. Segmentation Method Using Improved ACO

Medical image segmentation using the ACO can be considered a process in which ants are looking for similar pixels or food sources. These food sources are considered as threshold limits for image segmentation, and the optimal value of this threshold limit is determined after implementation of the algorithm.

At first, the whole image is divided into 3×3 windows. All ants are propagated uniformly and randomly on the whole MR image space to perform the search activity. For each of the targeted windows, a histogram curve is plotted based on the amount of pheromone trace. Based on groups of image pixels containing all, some, or none of the object, there are three possible scenarios analogous the entire window falls in background ,target or at the boundary of target and background.

Finally, the entire image is covered by searching ants and information for the whole image is saved in the histogram-storing ant's memory. The "food sources"—which are analogous to the different types of brain tissue white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF)—are then determined by the optimum results of the ACO algorithm. After defining the "food" in the memory of ants, they get involved in the task of finding pixels with the similar features to the food Probability of kth ant's movement from i to j can be calculated by

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

where $\tau_{i,j}$ is pheromone information in the previous loop while moving from node i to node j; η_{ij} is the value of heuristic function; N_i^k is the neighborhood nodes for the recent ant given that it is in the node i; the constants α and β influences the pheromone information and heuristic information respectively.

ACO is an iterative algorithm and two update operations are included in it. The updates are performed over the pheromone matrix. First update is done by all ants after each construction step (local pheromone update) to the last edge known to be traversed and second one after all ants have completed their one cycle of iteration by only one ant (offline pheromone update) .The local pheromone update is performed as followed by the equation:

$$T_{ij}=(1-\varphi).\tau_{ij}+\varphi.\tau_o$$

where $\phi \in (0, 1]$ is the pheromone decay coefficient and τ_o is the pheromone initial values.

The local update is performed to enable the search process more easy for next iterating Ants. The offline pheromone update is performed by the equation as follows:

$T_{i,j} = (1-\rho).\tau_{i,j} + \rho\Delta\, \tau_{i,j}$ if (i,j) belongs to best tour ;
$= T_{i,j}$ else

Pheromone evaporation causes the ants to search for some new paths and in this way provides opportunity to discover a new shorter path in the unexplored area during the whole search process. This is called"path exploration". Also it avoids the system a quick convergence towards a suboptimal path.

After the algorithm optimization has converged and the final criterion has been verified, segmentation of the image is complete.

Furthermore, in this algorithm the ant's decision to go to the next site is affected by ant's tendency to move to different orientations. The state of an individual ant can be expressed by its position (r) and its orientation (θ). The probability of ant's movement to other sites depends on the pheromone intensity in those sites and also the tendency to change its current direction w (Δθ).

The amount of pheromone distribution can be determined by equation

$$\rho(\tau) = \left(1 + \frac{1}{1+\delta\tau}\right)^{\beta}$$

where τ is the pheromone intensity in the next site, β controls ant's tendency to follow pheromone, and 1/δ is the sensory capacity, which shows that each ant's ability to sense pheromone decreases somewhat at high concentrations. Therefore, the moving probability of ant k from node l to i is calculated by

$$P_{li}^{k} = \frac{\rho_N(\tau_j)\times w(\Delta\theta_j)\times[\eta_j]^{\alpha}}{\sum_{j/l}\rho_N(\tau_j)\times w(\Delta\theta_j)\times[\eta_j]^{\alpha}}$$

j/l shows all nodes j in the neighborhood of node l. The heuristic function is mentioned as

$$\eta_i = \frac{1}{\varepsilon + d_i}$$

where ε is a small constant value and di is the absolute value of the difference between ith pixel's value and the average value of pixels on the current path.

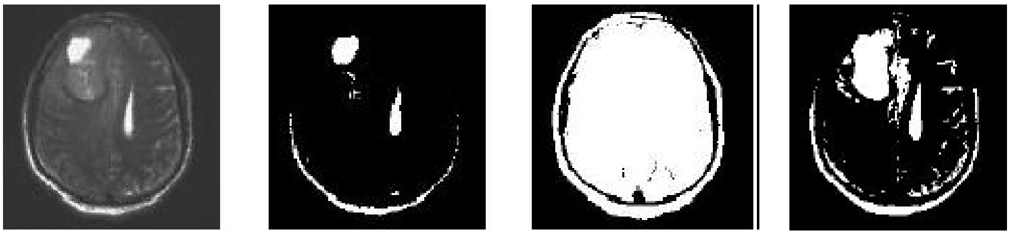
4. Implementation and Results

The proposed algorithm was implemented using MATLAB programming language on a computer with Core i3 2.5 GHz CPU and 2 GB RAM. The image acquired through Magnetic Resonance Imaging (MRI) was used for comparing the performances of the three methods. Time complexity of this algorithm depends on image size, number of algorithm iterations, number of ants and number of steps for each ant and other parameters.

ACO segmentation algorithm is evaluated using a number of performance metrics and compared to existing segmentation algorithms including the K-means and FCM algorithm. A cluster separation (CS) measure is used that is a function of the ratio of the sum of within-cluster scatter to between-cluster separation, reflecting the tissue segmentation.

Method	CS Measure (Mean and S.D.)
ACO	0.01656±0.00012
FCM	0.10147±0.00046
K-means	0.17254±0.00071

Fig.1 shows some brain images which contain tumors, and also results of the ACO algorithm and other approaches. As can be seen, in the ACO algorithm the region detected as tumor is more distinct, clear and without any extra margin which is usually caused by inflammation. The results are more accurate than other methods, but among other methods, FCM results are better than traditional k-means.



a. Original b.ACO improved c.K-means d.FCM

Fig. 1: Results of brain segmentation.

5. Conclusion

Detecting the existence of brain tumors from MRI in a fast, accurate, and reproducible way is a challenging problem. Most methods used currently are manual, computationally intensive, and inefficient and often require specially trained personnel to perform such tasks. This may not be practical particularly in urgent cases; thus, a more automated and efficient algorithm could be important for more widespread clinical implementation.

The ant colony optimization algorithm is designed to achieve ideal results for the segmentation of medical MR images and to do so in a computationally efficient fashion. ACO is a nature inspired algorithm. It takes into account the various advantage of ant colony like stigmergy, distributed computation, pheromone evaporation, decision-making based on pseudo-random proportional rule.

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