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IMPROVED MEDICAL IMAGE SEGMENTATION (IMIS) USING ADJUSTED ANT COLONY OPTIMIZATION WITH HIDDEN MARKOV RANDOM FIELD MODEL

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ABSTRACT

Segmentation and analysis of medical images is an important task for radiologists. Current segmentation methods have limitations such as long search time, high computation, and erroneous results. This paper presents an improved method for the caterpillar colony optimization segmentation method. In the first step, we propose a Hidden Markov Random Field Model with k-means clustering, which allows to quickly collect the ants to obtain the image threshold. In the next section, we use tuned Ant colony optimization to get the best results. The algorithm was tested on a small set of medical images in the database.

Keywords: Hidden Markov Random field model (HMRF-EM); adjusted ant colony optimization (AACO), Segmentation, Magnetic Resonance (MR) image, Improved Medical Image Segmentation (IMIS), Ant Colony Optimization (ACO).

INTRODUCTION

Dividing an image into its disjoint homogeneous region having similar objects of interest is referred as segmentation. The image property like pixel intensity is used to determine the extent of homogeneity. On the other hand, clustering techniques use optimal partitioning and develop subgroups of a given data. These subgroups correspond to the data points of similar characteristics. The two different subgroups correspond to the data points having minimum difference in their characteristics [1].

Some applications of image segmentation are Medical imaging, weather forecasting, object location & identification in satellite images, finger print and face recognition, Machine vision etc. Many algorithms exist for classifying the images as per the method implemented. But these methods or algorithms are generally combined with some other domain strategies to get the solution of a particular problem domain. For medical field, Magnetic Resonance (MR) image segmentation is proposed by various researchers for number of clinical investigations with varying complex situations. Medical image processing relates to radiology and the responsible person to analyze is radiologist. Radiologists are normally answerable for acquisition of medical images from diagnostic aspects, despite the fact that some interventions are performed by the radiologists during acquisition of the image.

MATERIAL AND METHODS

The proposed method consists of few different sections and hence discussed separately.

2.1Hidden Markov Random Field Model (HMRF)

MRF methods are widely used in computer diagnostics for medical image segmentation, surface reconstruction, and inference. The HMRF algorithm has been proven suitable for image segmentation working with pixel intensities. Some researchers have changed or modified the label construction X=(x1,…xn). where (x€L) and L correspond to all possible labels. Binary division, property changes such as L={0,1} change the division process. In the MAP criterion, the label X* is defined a

$$X^*=\operatorname{argmax}\{p(y|x,\theta),p(x)\} \tag{1}$$

Here p(x) denotes Gibbs distribution [2][3][14].

The EM Algorithm includes E-step and M-step. The conditional expectations with all possible configuration of labels Q(θ| θ(t)) is calculated using E-step.[2][3]

M-step is used to obtain next estimate by maximizing Q(θ|θ(t)) as

$$\theta(t+1)=\operatorname{argmax}Q(\theta|\theta(t)) \tag{2}$$

The Gaussian distribution function and probability distribution is obtained by Equation(3)& Equation(4)

$$G(z;\theta_l)=\frac{1}{\sqrt{2\pi\sigma^2 l}}\exp\left(-\frac{(z-\mu l)^2}{2\sigma^2 l}\right) \tag{3}$$

$$\begin{aligned} P(y|x,\theta) &= {}^{\pi}_{\pi}p(y_i|x_i,\theta_{xi}) \\ &= G(y_i|x_i,\theta_{xi}) \\ &= \tfrac{1}{Z}\exp\left(-U(y|x)\right) \end{aligned} \tag{4}$$

For using HMRF-EM algorithm, the initial labels are obtained by k-means clustering on grey scale intensity of pixels. The initial parameter θ(0)is obtained for EM algorithm and initial labels X(0) for MAP algorithm.

2.2 Ant Colony Optimization (ACO)

Basically, ACO was proposed by M. Dorgio to solve an optimization problem. ACO is an algorithm inspired by nature. The foraging behavior of ants is considered a key feature in optimizing the problem. The ant's communication strategy is carried out by the deposition of chemical space discharges called pheromones. Each ant serves for pheromones and stores their own pheromones after a visit, so pheromone regeneration occurs. [4]. An ant's movement increases its pheromone concentration, which increases the ability of other ants to follow the same path. Evaporation from the other ant reduces the pheromones on the other side[5]. The entire colony thus finds and follows the shortest route to a food source. When segmenting an image, we need to find the symbols that reflect the differences. Since the value of gray pixels is very different from the background and usually changes at edge points, it is used as an indication of clustering and the derivative of the points reflects the change [13].

2.2.1 Initialize and deploy ant:

Typically, the initial value of a pheromone is the same for all possible pixels. However, you can specify initial values with some basic information. Allows image preprocessing where the input may not be raw data. To obtain heuristic information, the distribution of neighboring pixels is shown in (Fig. 1).

	i-2,j-1		i-2,j+1	
i-1,j-2	i-1,j-1	i+1, j	i-1,j+1	i-1,j-2
	i,j-1	**Pixe l (i,j)**	i, j+1	
i+1,j-2	i+1,j-1	i-1, j	i+1,j+1	i+1,j+2
	i+2,j-1		i+2,j+1	

Figure.1Neighbors of Pixel (i,j)

2.2.2 Construction process:

In ACO, each pixel of the image is treated as an ant, and a 2D vector of HMRF-EM is built using the gray scale and the gradient as the MAP threshold. This two-dimensional vector is considered the initial pixel pheromone matrix [2][3]. Ant behavior-based segmentation is the process by which ants forage. The ant will stop wandering around the image when it encounters a pixel with a different characteristic. (i.e. pheromones). For a given image of size MxN, the probability of a pixel transition, i.e. each ant, is calculated by equation (5).

$$p_{(i,j)(l,k)} = \frac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum_{\in N_l^k} \tau_{ij}^{\alpha}\eta_{ij}^{\beta}} \tag{5}$$

Where τ_ijdenotes value of pheromone at node (i,j) and N (l,k) is the neighboring nodes of (l,k) i.e. l to k pixels within 12-neighbours of the pixel (l,k). 〖η〗_ij denotes heuristic information of pixels from i to j; α,and $\boldsymbol{\beta}$ are constants that controls the effect of pheromone and heuristic information in transition. The heuristic information at each node (i,j) is determined [6]as

$$\eta_{ij} = \frac{1}{z} V_c(I_{i,j}) \tag{6}$$

$$Z = \sum_{i=1}^{M}\sum_{i=1}^{N} V_c(I_{i,j}) \tag{7}$$

Where Z is a normalization factor to limit the values of p_ij within [0,1].I_(i,j)corresponds to intensity of the pixel (i,j) of the image I. Here I is treated as a function that indicates neighbor pixel relations and is represented by any of equations from 8-11 or similar ones. x is a gray scale value.

$$F(x) = \lambda x \quad for\ x \geq 0, \tag{8}$$

$$F(x) = \lambda x^2 for\ x \geq 0, \tag{9}$$

$$F(x) = \left\{ \sin\left(\frac{\pi x}{2\lambda}\right) for\ 0 \leq x \leq \lambda \right. \tag{10}$$

$$F(x) = \left\{ \frac{\pi x \sin\left(\frac{\pi x}{\lambda}\right)}{\lambda} for\ 0 \leq x \leq \lambda \right. \tag{11}$$

In the final stage of construction process, ant tends to death by arriving to one of its previous visited node or pixel. Ant can escape their death according to dynamic neighborhood pixel probability. The ants escape ratio increased to 50%.This is done by increasing neighboring pixels from 8 to 12 (Figure2)

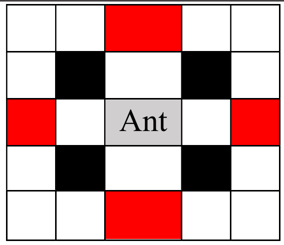

Figure2: Increasing neighboring pixel to 12 pixels for each Ant

Pheromone Update Process:

Update process in ACO is done in two stages. In first stage, ant's deposit pheromone on to the node after their visit and secondly this deposited pheromone gets evaporated. This combined activity corresponds to the quantity of pheromone updated on each path travelled by the ant's. The quantity of pheromone on each pixel(i,j) is updated using Equation(12)

$$\tau_{ij} = (1-\rho)\tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \qquad (12)$$

Where ρ is pheromone evaporation coefficient & m is number of ant's. 〖Δτ〗 _ij^k is obtained from heuristic matrix η_(i,j) i.e. from Equation (13)

$$\Delta\tau_{ij}^{k} = \eta_{i,j} \qquad (13)$$

This heuristic information of kth ant is updated in ant's memory and used for further process. When all ant's traverse to neighboring pixel and reaches to its start, it dies. The radius of travelled path is considered as distance travelled by kth ant. This area is computed by a ratio of Euclidian distance between the two pixels (Lk) to the total number of pixels(Sk) i.e. (Lk/Sk).

Decision Process:

This is a crucial process, in which with reference to previous steps, it is decided at each pixel whether it is an edge or not. The edge information is determined with the help of threshold (MAP) values obtained by HMRF algorithm [2][3]. This threshold matrix (T) is considered as initial pheromone matrix. Based on the iterative method proposed in [7][8], the mean above (T) and mean below (T) computed. For each pixel (i,j), if the pheromone value associated is greater than (T), then edge detected otherwise non edge detected. This is defined by the following equations:Equation (14)& Equation (15)

$$T^{(0)} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\tau_{i,j}}{MxN} \qquad (14)$$

Where T(0) is the average of averages above threshold TA and below threshold TB.

$$T_{(i)} = (T_A + T_B)/2 \qquad (15)$$

Finally, the mean of these two averages are taken as above Equation (15). The stopping condition of this algorithm is defined when two consecutive threshold values T(i) are similar. This indicates that there will not be any new edge further.

EXPERIMENTAL RESULTS

To analyze the performance, proposedACO algorithm is tested for some of the medical images among the data base available. To demonstrate the result, one of the Breast MR images is chosen for segmentation. The experiment is performed on Intel PC (Pentium 4, 2.2GHz, 2G RAM). Fig.

3 (a) shows the original MR image of Breast of size 128x128 grayscale with intensity values from 0 to 255 chosen for test experiment. For segmentation purpose, the threshold values are obtained with HMRF_EM algorithm with k-means clustering for k=3.

(a) (b) (c)

Figure. 3: a) Original Medical Image, b) and c) Segmentation Results

The segmentation result of our algorithm is shown in (figure 3(c)) in which edges are preserved more precisely. The segmentation result is obtained for 12 neighborhood pixels. For experiment, medical image data base of more than 100 images is created in consultation with a senior radiologist. A sample result for one of the medical image is shown in (Figure 3). It has been observed in the result of old ACO algorithm (figure 3(b)) that, if the gray intensity of target and background are same, then edges are not preserved and has low continuity with missed edge detection. On the other hand the proposed improved algorithm can better detect the edge. It improves the result by effectively compensating the discontinuity of image edge (figure 3(c)), greatly reduces execution time, and improves efficiency of execution of algorithm.

4 CONCLUSION

In medical image segmentation, old ant colony algorithm has limitations of long searching time, rigorous calculations hence produces inappropriate results. The improved ant colony algorithm proposed in this paper for medical image segmentation has comparatively high efficiency and better edge detection. The important modifications in this algorithm includes (a) in the initial phase of segmentation, we introduced the idea of HMRF-EM with k-means clustering to get threshold values. This enables ants to gather quickly at the edge of the image. (b) In this phase, we have modified an edge search method by changing neighborhood pixels from 8 to 12.The result of experiment performed proves that, the proposed improved algorithm is capable of segmenting the given image more efficiently.

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