An Improved Ant Colony Algorithm Optimization for Automated MRI Segmentation Using Probabilistic Atlas

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Abstract— **Segmentation plays a crucial role in image processing, especially in medical image analysis which encompasses an extensive range of image formation modalities including Magnetic Resonance Imaging (MRI). In this paper, a fully automated segmentation of brain MR images is presented. The proposed approach is an improved version of ACO (Ant Colony Optimization) algorithm conflating with the a prior probability atlas images of gray matter, white matter and cerebrospinal fluid to robustly segment the brain MR images. The ACO optimization algorithm is inspired by the natural food-searching behavior of some ant species. Ants retrace the pheromone trial on the ground which deposited by their other colony members while walking and foraging. The propounded improved ACO-Atlas based segmentation algorithm is qualified to generate three different pheromone matrices that each of which corresponds to a brain tissue class. The establishment of the pheromone matrix is based on the randomly scattered ants' movements on the MR image. Furthermore, these movements are steered by the local statistical moments of the MR image's intensity values. Experiments are done to demonstrate the effectiveness and high accuracy of the proposed method.**

Keywords- MRI, Ant colony optimization, Segmentation, Probabilistic Atlas, Statistical central moments

I. INTRODUCTION

Magnetic resonance imaging (MRI) techniques provide excellent differentiation and visual resolution of brain tissue types in vivo [1]. Fundamental step in the analysis of MR brain images is segmentation in to different intensity classes which are regarded as the best available representations for biological tissues [2]. While there is no universal theory for segmenting MR brain images, strategies to segment and visualize the brain structures are of immense value in basic and clinical neuroscience for detecting tumors, edema, and necrotic tissues, in order to prescribe appropriate therapy [3,4]. Great interest has been shown in the area of MR brain image segmentation and numerous approaches have been proposed, including thresholding, region-growing, edge detection and clustering. For many years now, several papers highlighted the efficiency of techniques inspired from the nature [5]. In the category of nature inspired approaches, one novel effectual powerful algorithm stands out Ant Colony Optimization. First to provide detailed analysis and theoretical background was Dorigo et al., providing results and working Ant system model [6,7]. Since then, many diverse variants of the basic principle have been reported in the literature, Max-Min ant system and the ant colony system, to name but a few. ACO has been widely applied in various problems [8]. Due to the fact that healthy brain tissue can generally be classified into three broad tissue types on the basis of an MR image, which are grey matter (GM), white matter (WM) and cerebrospinal fluid (CSF) [9], the approach proposed here takes the knowledge of the spatial distribution of these three main tissue types in the form of a prior probability images and also the advantages of ant colony optimization (ACO) algorithm of Tian et al [8]., with modifications in pheromone matrix and heuristic function, to segment the brain MR images in order to separate WM, GM and CSF. By knowing the prior spatial probability of each voxel being grey matter, white matter or cerebrospinal fluid, it is possible to obtain a more robust classification [9]. To the best of authors' knowledge, the most of ACO algorithms which deployed in image processing are circumscribed to image edge or shape detection. Furthermore, there has been minute research work on using ACO in medical image segmentation, including MR brain images, except [10] and [11], whereas there is intrinsic distinction between our proposed methods and theirs. Since none of these paper segmented the brain MR image in to the three main brain tissues, while the results of our proposed method are segregated three main brain tissue clusters. The configuration of this paper is as follows; Section 2 gives an overview of ant colony optimization algorithm in general. The brain MRI segmentation method using proposed improved ACO algorithm and probabilistic atlas is described in section 3. Section 4, discusses on the improvements mentioned in previous section. Next, in section 5, the experimental results are presented. Finally, section 6 concludes the paper.

II. ANT COLONY OPTIMIZATION ALGORITHM

Ant colonies, and more generally social insect societies, are distributed system that in spite of the simplicity of their individuals, present a highly structured social organization. As a result of this organization, ant colonies can accomplish complex tasks in some cases far exceed the individual capabilities of a single ant [12]. The field of ant algorithms studies models derived from the observation of real ants' behavior, and uses these models as a source of inspiration for the design of novel algorithms for the solution of optimization and distributed control problems [12].

In the category of the most successful examples of ant algorithms, ACO illustrates the point, which is used in this study. ACO is inspired by the foraging behavior of some ant colonies, and targets discrete optimization problems. This foraging behavior is based on indirect communication mediated by chemicals produced by the ants, which are called pheromones. While walking from food sources to the nest and vice versa, ants deposit pheromones on the ground, forming in this way a pheromone trail. Ants can smell the pheromone and they tend to choose, probabilistically, paths marked by strong pheromone concentrations [12]. And the more ants choose the path, the stronger the pheromone concentration. Thus the pheromone trail can help the ants find quickly the shortest way (the most preferred way) to the food sources [13]. Ant colony optimization exploits a similar mechanism for solving optimization problems. To be more specific, ACO is an iterative algorithm [15] which aims to discover the optimal solution of the target problem over solution space, a weighted graph [8], which consists of nodes and edges by constructing candidate solutions via a pheromone model, that is, a parameterized probability distribution over the solution space. In other word, the movement of the ants is probabilistically dictated by the transition probability which reflects the likelihood that an ant will move from a given node to another. This probability is influenced by heuristic information and pheromone information [8]. The former is problem specific and the latter is constructed and updated during the search and is called pheromone matrix. Consider totally K ants are applied to find the optimal solution in a space χ that consists of ($M_1 \times M_2$) nodes. The procedure of ACO iterates over three phase as follows [8, 15].

–Step one: In this step the positions of totally K ants, as well as the pheromone matrix $\tau^{(0)}$ and parameters are initialized.

– Step two: For the construction-step index n=1: N

- For the ant index k = 1: N
  - Consecutively move the k[th] ant for L steps according to a probabilistic transition matrix $p^{(n)}$,(with a size of $M_1M_2 \times M_1M_2$).
- Update the pheromone matrix $\tau^{(n)}$.

– Step three: Make the solution decision according to the final pheromone matrix $\tau^{(N)}$.

The establishment of probabilistic transition matrix and the update of the pheromone matrix are of immense value in the ACO algorithms which are described as follows: At the n[th] construction-step of ACO, the k[th] ant moves from the node i to the node j according to the transition probability $p_{i,j}^{(n)}$, the probability that an ant in node i will move to node j, which is the basis of decision rule is determined by:

$$p_{i,j}^{(n)} = \frac{\left(\tau_{i,j}^{(n-1)}\right)(\eta_{i,j})^{\beta}}{\sum_{j\in\Omega_i}\left(\tau_{i,j}^{(n-1)}\right)(\eta_{i,j})^{\beta}} \qquad (1)$$

Where $\tau_{i,j}^{(n-1)}$ is the quantity of pheromone on the traverse linking the two nodes, i and j. $\eta_{i,j}$ represents the heuristic information for going from node i to node j, which is fixed to be same for each construction step. Ω_i is the neighborhood nodes for the ant which is on the node i. The constant α and β control the influence of the pheromone update. To be more specific, it is performed by all the ants after each construction-step. The pheromone matrix is updated as:

$$\tau^{(n)} = (1-\psi).\tau_{i,j}^{(n-1)} + \psi.\tau^{(0)} \qquad (2)$$

where $\psi \epsilon (0\ 1]$ is the pheromone decay coefficient, and $\tau^{(0)}$ is the initial value of the pheromone. The second update performed at the end of the construction process which is called offline pheromone update and its formula is cited as:

$$\tau_{i,j}^{(n-1)} = \begin{cases} (1-\rho).\tau_{i,j}^{(n-1)} + \rho\ .\Delta\tau_{i,j}^{k} & if\ (i,j)\ belongs\ to\ the\ best\ true \\ \tau_{i,j}^{(n-1)} & otherwise \end{cases} \qquad (3)$$

where ρ is the evaporation rate. Moreover, the determination of best tour is subject to the user-defined criterion, it could be either the best tour found in the current construction-step, or the best solution found since the start of the algorithm, or a combination of both of the above two [8].

III. THE PROPOSED MRI SEGMENTATION ALGORITHM USING IMPROVED ACO BASED ON PROBABILISTIC ATLAS

The approach which is propounded in this paper aims to segment the MR brain image into three separate classes, using ACO and the prior spatial probability of each voxel being GM, WM and CSF. In order to segment the brain MR image by ACO, the proposed approach deploys a number of ants and dispatches them three times

according to three different rules to crawl on an image for constructing three distinct pheromone matrices. The aggregation of ants represents the segmented brain MR image. Furthermore, local variation of the MR image's intensity navigates the movements of the ants. The proposed method here, utilizes spatial maps of prior probabilities of the voxel belonging to the GM, WM and CSF classes. This information is in the form of probability images provided by the Montreal Neurological Institute as part of the ICBM, NIH P-20 project (Principal Investigator John Mazziotta), and derived from scans of 152 young healthy subjects [9], [16] and [17]. These probability images contain values in the range of zero to one, representing the prior probability of a voxel being GM, WM or CSF after an image has been normalized to the same space (Fig. 1) [9]. Thanks to the prior knowledge, it is possible to obtain a more robust classification [9]. In order for the proposed algorithm to work properly, the MR image must be in register with the prior probability images. This registration is automatically done by SPM (Statistical Parametric Mapping) [19]. The rest of the procedure is repeated three times to achieve the GM, WM. and CSF. The initialization process commences and after that the approach runs for iterations to construct the pheromone matrix by iteratively executing not only the construction process but also the update process. Ultimately, the decision process is preformed.

A. Initialization Process

Totally k ants are randomly assigned on an image I with a size of $M_1 \times M_2$, each pixel of which can be viewed as a node. Furthermore, each component of pheromone matrix $\tau^{(0)}$ must be set. The prevalent view for setting the pheromone matrix is to adjust its elements to be a constant which leads to MR edge detection, whereas we have designated another strategy to segment the MR image. More explicitly, thanks to the prior probability images, we take cognizance of the spatial distribution of the voxels which belongs to a class such as GM. Consequently, each component of pheromone matrix is proposed to be a proportion of the related prior probability atlas. Since this scheme steers the ants' movements from the primary step the invaluable consequence which is less executing time, is expected.

B. Construction Process

At the n^{th} construction step, one ant out of the total k ants is randomly selected, and this is subject to move on the image for L movement-step. This ant moves from the node (l,m) to its contiguous node (i,j) according to a transition probability which is determined as

$$p_{(l,m)(i,j)}^{(n)} = \frac{\left(\tau_{i,j}^{(n-1)}\right)^{\alpha}(\eta_{i,j})^{\beta}}{\sum_{(i,j)\in\Omega_{(l,m)}}\left(\tau_{i,j}^{(n-1)}\right)^{\alpha}(\eta_{i,j})^{\beta}} \qquad (4)$$

where $\tau_{i,j}^{(n-1)}$ is the pheromone value of the node (i,j), $\Omega_{(\mathrm{l,m})}$ is the contiguous nodes of the node (i,j), $\eta_{i,j}$ stands for the heuristic information by

$$\eta_{(i,j)} = \frac{1}{d_{(i,j)}} \qquad (5)$$

where $d_{(i,j)}$ is the distance between the two nodes. However, there are some other one who support to determine the heuristic information by the local statistics at the pixel position (i,j) as

$$\eta^{(i,j)} = \frac{1}{Z} V_c(i,j) \qquad (6)$$

where $Z = \sum_{i=1:M_1} \sum_{j=1:M_2} V_c(i,j)$ which is a normalization factor. $I(i,j)$ is the intensity value of the pixel at the position (i,j) of the image I, the function $V_c(i,j)$ is a function 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 [8]. This idea is preferred to utilize in this paper. Like [8], for the pixel under consideration, the function $V_c(i,j)$ is defined as:

$$\begin{aligned} V_c\left(I_{(i,j)}\right) = f(\ & \left|I_{i-2,j-1} - I_{i+2,j+1}\right| + \left|I_{i-2,j+1} - I_{i+2,j-1}\right| \\ & + \left|I_{i-1,j-2} - I_{i+1,j+2}\right| + \left|I_{i-1,j-1} - I_{i+1,j+1}\right| \\ & + \left|I_{i-1,j} - I_{i+1,j}\right| + \left|I_{i-1,j+1} - I_{i-1,j-1}\right| \\ & + \left|I_{i-1,j+2} - I_{i-1,j-2}\right| + \left|I_{i,j-1} - I_{i,j+1}\right| \ ) \end{aligned} \qquad (7)$$

Four functions are selected to consider as the function $f(0)$ in above equation [8] which are as follows:

$$f(x) = \lambda x \quad for\ x \geq \lambda \qquad (8)$$

$$f(x) = \lambda x^2 \quad for\ x \geq \lambda \qquad (9)$$

$$f(x) = \begin{cases} \pi x \sin\left(\frac{\pi x}{2\lambda}\right) & 0 \leq x \leq \lambda \\ 0 & else \end{cases} \qquad (10)$$

$$f(x) = \begin{cases} \pi x \sin\left(\frac{\pi x}{2\lambda}\right)/\lambda & 0 \leq x \leq \lambda \\ 0 & else \end{cases} \qquad (11)$$

where λ adjusts the functions' respective shapes (Fig. 2) [8]. Among the above functions, the first and third ones results in better effects (Fig. 4). In addition to the above functions, the heuristic information is propounded to be the local statistical moments in this paper. More specifically, since a smooth region contains pixels with values close to each other and a rough region has wide variability in pixel values [handbook], local statistical moments

of the image can be used as a texture metrics in order to define the heuristic information. Therefore, we scrutinize the local different orders of central moment. In general, the central moment of order k(2−4) of a distribution is defined as:

$$m_k = E(x-\mu)^k \qquad (12)$$

where $E(x)$ is the expected value of x and μ is the mean [20]. The permissible range for the ant's movement is the second issue to be considered which is determined to be like [8] either the 4-connectivity neighborhood or the 8-connectivity neighborhood (Fig.3).

C. Update process

The algorithm possesses two level updates operations for updating the pheromone matrix, one is *global* and the other is *local*.

1. The global pheromone update this level of pheromone updating process is carried out after the movement of each ant within each construction step.

Each component of pheromone matrix is updated according to [8],

$$\tau_{i,j}^{(n-1)} = \begin{cases} (1-\rho).\tau_{i,j}^{(n-1)} + \rho\,.\Delta_{i,j}^{(k)} & if\ (i,j)\ is\ visited\ by\ the\ current\ k-ant \\ \tau_{i,j}^{(n-1)} & otherwise \end{cases} \qquad (13)$$

where ρ is defined in (3) previously, $\Delta_{i,j}^{(k)}$ i,j is equal to heuristic matrix $(\eta_{(i,j)})$.

2. The local pheromone update the local level of updating the pheromone matrix is preformed after the movement of all ants within each construction step with the ψ given in (2) is defined as: [8]

$$\tau^{(n)} = (1-\psi).\tau^{(n-1)} + \psi\,.\tau^{(0)} \qquad (14)$$

D. Decision process

After the three previous steps, in order to educe commensurate cluster, making a decision on the updated pheromone matrix τ (n) is inevitable. Hence, an efficient approach to adaptively search for the global threshold T of the last pheromone matrix using the Otsu's method is deployed [8], [21].This method involves iterating through all the possible threshold values and calculating the statistic criterion, here the mean, for the pixel belongs to each side of the threshold. The schema of the mentioned algorithm is as follow. First of all, the initial threshold T0 is defined as the mean value of the pheromone matrix. Secondly, the pheromone matrix elements are categorized into two classes according to the criterion whether its value is less than T0 or not. Thirdly, the average of two mean values of each of above two categories is defined as the new threshold. Finally, the two former steps are reiterated until the threshold value does not change any more (based on a user-defined tolerance).

IV. DISCUSSION ON THE PROPOSED METHOD

In order to ensure that the proposed definition of the heuristic information would led in the better results, we compare our method (modifying the initialization of pheromone matrix is neglected) with that of Tian et al. [8], For this purpose both methods were executed on benchmark images, such as Lena and Cameraman. As Fig. 4 and Fig. 5 illustrate our results is not only as well as theirs but also better than Tian et al.'s [8]. What's more, the invaluable consequence of our modified heuristic function is the convergence time of the algorithm which is one order of magnitude less than Tian et al.'s method. Consequentially, the proposed heuristic function is decently replaced with the former one for the rest of the algorithm.

V. EXPRIMENTAL RESULT

To demonstrate the effectiveness of the proposed algorithm, simulated brain MR image and its manual is downloaded from the Brainweb [22]. Since Brainweb provides a simulated brain database (SBD) including a set of realistic MRI data volumes produced by an MRI simulator, a simulated T1 weighted MR (256×164×256) image from 0% of noise and 0% of intensity non-uniformity was downloaded from Brainweb (Fig. 6) [22], [23], [25]. The simulated MR and its manual segmented images are registered to the ICBM atlas prior to the execution of the segmentation algorithm using SPM toolbox and mutual information registration [19]. The parameters' values are equal to those of Tian et al., except the initial value of the pheromone matrix and heuristic function. The three distinct brain tissue, including WM, GM and CSF is extracted by the proposed algorithm. As Table 1 demonstrates the mean specificity, sensitivity and accuracy [27], [28] are used to evaluate the performance of our proposed algorithm. According to table 1, our proposed method is successful in segmenting the simulated MR brain image with the mean accuracy 96.31 percent.

VI. CONCLUSION

An improved ACO algorithm using probabilistic atlas is proposed to segment MR brain images. Prior to evaluate the performance of the propounded method on brain MR images, two benchmark images were used to demonstrate the efficiency of the algorithm in edge detection. Experimental results illustrate the feasibility and high accuracy of the algorithm in segmenting the gray matter, white matter and cerebrospinal fluid of the simulated brain MR image. In the assessment of the method the effects of noise and intensity non-uniformity are not consider which will be study in the future works. To conclude, the proposed method is capable to segment the brain MR images.

TABLE I. SEGMENTATION EVALUATION ON SIMULATED T_1 BRAIN MR IMAGE.

Evaluation parameters %	***White mater***	***Gray mater***	***CSF***
Sensitivity	95.54	99.98	98.76
Specificity	82.19	82.39	91.35
Accuracy	96.26	93.29	99.38

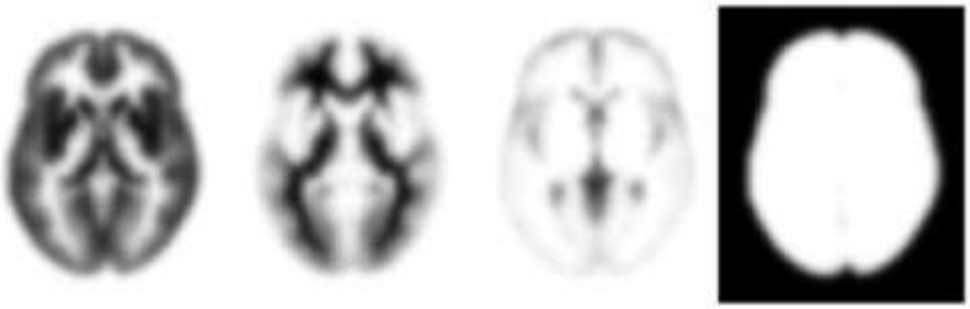

Figure 1. The prior probability images of GM, WM, CSF and none brain tissue. Values range between zero and one [8]

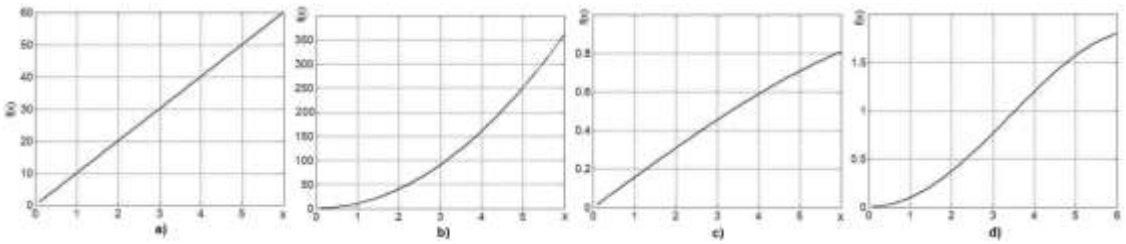

Figure 2. Various functions with the parameter λ = 10; (a), (b), (c) and (d) are the functions defined in (8), (9), (10) and (11) [8]

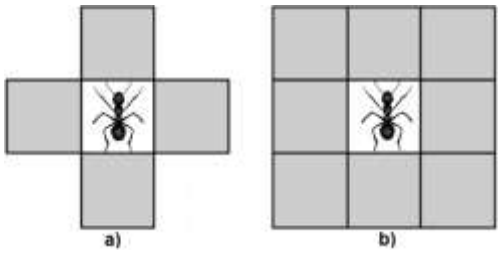

Figure 3. (a) 4-connectivity neighborhood and (b) 8-connectivity neighborhood of the current position of the ant I(i,j)

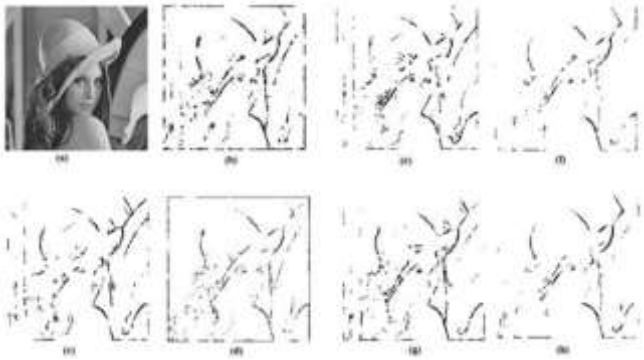

Figure 4. Different edge extracted image of the Lena benchmark image, (a) The original image. (b) The proposed improved ACO image edge detection algorithm with the central moment of second order as a heuristic function (c) The proposed improved ACO image edge detection algorithm with the central moment of third order as a heuristic function. (d) The proposed improved ACO image edge detection algorithm with the central moment of forth order as a heuristic function. (e) − (h) The Tian et al.'s method with the heuristic function defined in (8) − (11), respectively

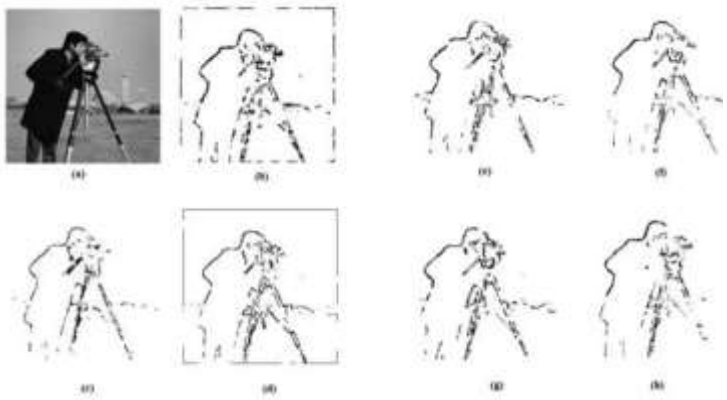

Figure 5. Different edge extracted image of the Cameraman benchmark image. (a) The original image. (b) The proposed improved ACO image edge detection algorithm with the central moment of second order as a heuristic function (c) The proposed improved ACO image edge detection algorithm with the central moment of third order as a heuristic function. (d) The proposed improved ACO image edge detection algorithm with the central moment of forth order as a heuristic function. (e) − (h) The Tian et al.'s method with the heuristic function defined in (8) − (11), respectively.

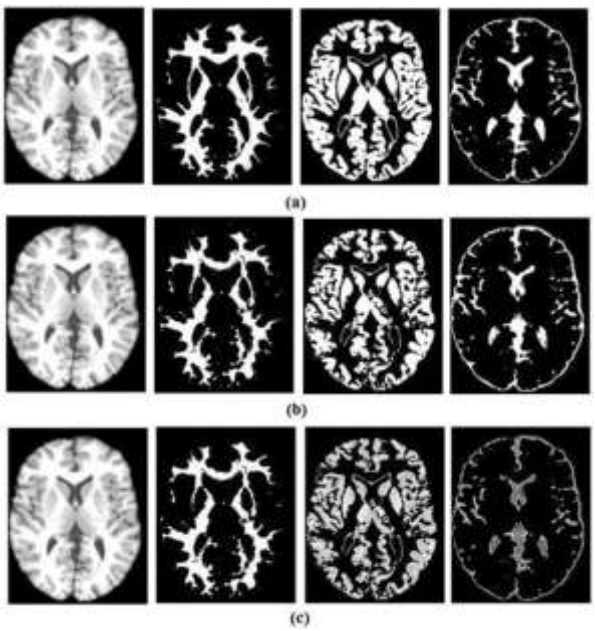

Figure 6. From left to right, original brain MR image, white matter, gray matter and cerebro-spinal fluid (a) discrete anatomical model of the original image, (b) binary segmented image of the proposed method (c) gray level segmented image of the proposed metho

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