Medical Image Segmentation using a Multi-Agent System Approach

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Abstract: *Image segmentation techniques have been an invaluable task in many domains such as quantification of tissue volumes, medical diagnosis, anatomical structure study, treatment planning, etc. Image segmentation is still a debatable problem due to some issues. Firstly, most image segmentation solutions are problem-based. Secondly, medical image segmentation methods generally have restrictions because medical images have very similar gray level and texture among the interested objects. The goal of this work is to design a framework to extract simultaneously several objects of interest from Computed Tomography (CT) images by using some priori-knowledge. Our method used properties of agent in a multi-agent environment. The input image is divided into several sub-images, and each local agent works on a sub-image and tries to mark each pixel as a specific region by means of given priori-knowledge. During this time the local agent marks each cell of sub-image individually. Moderator agent checks the outcome of all agents' work to produce final segmented image. The experimental results for CT images demonstrated segmentation accuracy around 91% and efficiency of 7 seconds.*

Keywords: *Medical image segmentation, agent, multi-agent system.*

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1. Introduction

Image segmentation techniques have been an invaluable task in many domains such as quantification of tissue volumes, medical diagnosis, pathological localization, anatomical structure study, treatment planning, partial volume correction of functional imaging data, and computer integrated surgery [16]. Image segmentation separates an image into some disjoint partitions whereas the whole of partitions reconstruct the primary image. Image segmentation is still a debatable problem while there have been done many research work in the last few decades [15]. Firstly, every solution for image segmentation is problem-based. Secondly, medical image segmentation methods generally have restrictions because medical images are very similar in gray level and texture among the interested objects. Therefore, significant segmentation error may occur.

Bearing in mind the above obstacles of medical image segmentation, our new algorithm based on Multi-Agent system is proposed. An agent is defined with some properties to perform segmentation over time. Due to the automatic nature of agent, it is suitable for segmenting images with high complexity. The goal of the agent is to find out appropriate label for each pixel in image. Firstly, Moderator agent creates and initializes the agents within image. The agent takes a sub-image and applies some values. The input image is divided into several sub-images, and each agent works on it and tries to mark each pixel in sub-images by means of given priori-knowledge. During this time the local agent marks each cell of sub-image individually. Finally, Moderator agent checks the outcome of all agents' work to produce final segmented image.

The main purpose of this work is to segment medical images simultaneously with some different regions of interest. This is a significant advantage compared to other approaches because it can segment many objects within an image concurrently.

We present a short description of Multi-Agent System (MAS) and agent properties in section 2. Section 3 reviews the pervious work in image segmentation using agents. Section 4 gives the details of our approach and discusses algorithms used in this research. Section 5 analyses the experimental results. Finally, section 6 concludes our work.

2. Background

2.1. Agent and Multi-Agent Systems

Although the terms of agent and multi-agent are used by many people who work in closely related areas, there is no universal definition of these terms. Some attributes of agent are similar in many literatures. The following properties are represented for a hardware or software-based computer system agent [13, 21]:

- *Autonomy:* Agents accomplish their goal without the direct interposition of human, control over their actions and internal state.
- *Social Ability:* Agents cooperate with other agents and maybe humans.
- *Reactivity:* Realizing their environment, and

responding to changes that occur in it.
- *Pro-activeness:* Having ability to exhibit goal-directed behaviour by taking the initiative.
- *Robustness:* Be prepared to learn and to recover from failure.

The other properties of agent which relate to its context are mobility, veracity, benevolence, and rationality [22]. The internal structure of an agent may consist of several units as shown in Figure 1 [17]:

- Input units, for receiving incoming data.
- Output units, for delivering agent's results.
- Planning units, for determining the processing strategy.
- Evaluation units, for checking the quality of the processing operations.
- Learning unit, for knowledge acquisition and adaptive behaviour.
- Control units, which implement the plan elaborated by the planning units, and coordinate the execution.

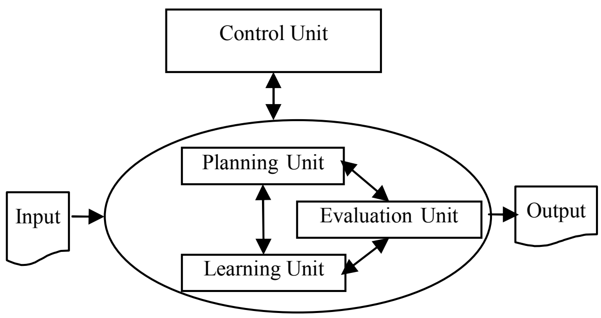

Figure 1. Internal structure of a typical agent.

Multi-agent system is overall a system with several entities which they have some mutual behaviour like cooperation, coordination and negotiation. In [12] multi-agent systems are suitable for problem solving with multiple methods and entities. They have the advantage of distributed and concurrent problem solving. Therefore in multi-agent system every entity has knowledge about their environs by cooperation, coordination and negotiation to achieve goal quickly. The multi-agent system is broadly used in variety fields such as robotic and imaging due to their ease of construction and maintenance, parallel architecture benefits, heterogeneous problem solving, and reliability [7].

3. Literature Review

However, many methods have been proposed for image segmentation, thresholding, region growing, classifiers, clustering, deformable models, and neural networks, but it is obvious to use other methods for conveying the some drawbacks of mentioned methods. However each method has been further developed to produce better results, but using the other system for segmentation is evidently [4]. In this section, some recent researches have been elaborated. Finally, they are compared with traditional methods to show the achievement of multi-agent approaches.

Spinnu *et al.* [19] proposed a multi-agent approach to edge detection in medical images. They have defined two basic agent types; Knowledge Servers (KS), and Knowledge Processors (KP). KS agents manage the problem elements that are represented by objects and attributes. KP agents manage the processing and reasoning methods. Any agent may get or set attribute values, create or delete object instances and modify system configuration as well by dynamically creating new agents The proposed method achieves to its goal properly. But, there are some other improvements to reach the optimal solution. For example localization error can be taken in formulation error. Also, the contrast characteristic could be used in addition of noise and texture characteristics.

Boucher *et al.* [2, 3] proposed MAS to segment image of the living cells. This type of the image has four different regions; nucleus, pseudo-pod, white halo and background. Therefore, these components determine the type of the agents. Also, the internal manager agent is used which manages the execution of the agents. The segmentation is based on region-growing approach. Every agent assesses the four neighbour pixels. An evaluation function used for deciding the highest evaluation pixel. This function uses six criteria such as variance similarity, compact, gray level similarity, gradient direction similarity, and cell and nucleus image thresholding. If a pixel is labelled by two different types of agents then this pixel is added to event list of the manager. As a consequence, the proposed method is adaptable to the shape and size of the living cells to distinguish them from image. Also, this method provides richness information from images. This richness comes from the outcome of each agent in duration of its adaptability.

Liu and Tang [14] proposed MAS to segment a MRI image of brain. The brain has the four basic elements; like as outline, branching region, enclosing region and tumour region. For detecting each four regions, they assign some threshold range. The agent behaviour is one of these four types: breeding, pixel labelling, diffusion, and decay. Breeding means when an agent is in a homogeneous segment it should be produce some new agents in neighbourhood pixel. The significant difference in this paper is that the neighbourhood region is determined by a sector of a circle with specified radius. Diffusion is finding new homogeneous-segment pixels by moving to neighbourhood pixel. When an agent encounters with new pixel from an existed homogeneous segment, this agent label this pixel and it will become inactivated. Agents must be vanished or decayed after each of them passes its life span. The proposed method has less computation time in comparison with conventional method. However, there is problem to distribute agent over image optimally.

Germond *et al.* [11] proposed a framework which composed of MAS, a deformable model, and an edge detector for segmenting MRI image of brain. There are three different types of agents; region agent, edge agent, and scheduler. The region agents specialize for gray matter or for white matter segmentation. Edge agents specialize for the brain boundary detection. The agents are autonomous and concurrent. A shared memory is used for communicating of the agents. The MAS carries out segmentation of MRI scans. The proposed method uses seeded-region-growing method, a priori domain knowledge, and a statistical method whose parameters are acquired at run time. The aim of the deformable model is to detect the general boundary of the brain. And the edge detector module is used for its ability to detect a precise and robust localization of the boundaries for the all edges in a given image. As a result, the proposed method has the mean quality percentage of 96%. However, the method needs considerable user interaction.

Duchesnay *et al*. [9, 10] proposed MAS to organize and structure the knowledge according to irregular pyramid, the used image is mammography. The pyramid is a stack of the graphs recursively built from base to the apex and it provides removing geometrical constraint due to the fixed structure of the neighbourhood. This methods have two different types of the agent; region agent, edge agent. The agents can use seven behaviours; territory marking and feature extraction, exploration, merging planning, cooperation and negotiation which are consisted decimation, reproduction and attachment. The procedure of this framework is as follow. First, the image separated into two partitions and several agents are stayed at different part of the image. After that every agent seeks features around it and decides to merge with other agent based on similarity in features. In some cases the agents cannot decide due to the specified threshold is not fixed. Therefore, the agents cooperate and negotiate with the other agent of the same type how can decide for merging. The all behaviours of the agents are presented. Accordingly, the proposed method does not require substantial tuning effort. In addition, it is completely autonomous. Furthermore, it is not required priori information to segment images. Another interesting result is that this method can be used to segment some different images as well.

Richard *et al*. [18] proposed MAS which the aim is to segment the brain MR images. The framework is based on parallel execution of the agents. System manager launches agent executions in a sequential way. The agents are autonomous and have ability of the cooperation. In their framework, three types of the agents coexist such as global agent, local agent, and tissue-dedicated agents. They acquire the tissue models from the neighbourhood and label the voxels using a region-growing process. The proposed method shows the correct estimation of the tissue-intensity distribution in different locations in the image, despite large intensity variations inside the same tissue. In comparison with the other methods, the proposed method has the significant performance in spite of the increasing non-uniformity of intensity.

Benamrane and Nassane [1] proposed a multi-agent approach permitting segmenting brain MRI. They used two main types of the agent; global agent, and region agent. Global agent has three basic behaviours; initial segmentation, creating and launching the region agents, and coordinating of the region agents. The framework is based on three steps. Firstly, the global agent segments image by region growing approach. Secondly, the intermediate segmentation of the initial image will be merged by iterative merging of the initial regions from the previous step. Finally, segmentation of the intermediate segmentation by iterative merging of the intermediate regions is obtained using a fusion criterion. The proposed method has had acceptable results; each region presents clear cut limits, particularly the tumour regions which are correctly detected. However, the execution time is exceedingly high.

Table 1 shows the comparison between multi-agent and non-agent segmentation methods based on researchers and the image modality of each research.

Table 1. Comparison between multi-agent and non-agent segmentation methods.

Researchers	Image Size and Modality	Comparison with Non-Agent Methods
Spinnu et al.	Muscle cell and MRI	Can find the optimal solution properly.
Boucher et al.	Living cells	The method is adaptable and the result has rich information.
Liu an Tang	MRI of brain 612×792	Less computation time. Agent distribution is not optimal.
Germond L. et al.	MRI of brain	The mean quality percentage is equal to 96%. Considerable user interaction.
Duchesnay et al.	192×192 images including both medical and non-medical one	The approach does not require substantial tuning effort and it is completely autonomous. Not required priori information.
Richard et al.	MRI of brain	Adaptation to intensity non-uniformity and noise.
Benamrane and Nassane	MRI of brain that contains tumours	Good success in image includes heterogeneous, local and repartee information.

4. Methodology

The autonomous agent has already been used in image processing task where it discussed in section 3. In this section, a different multi-agent system is proposed for segmenting medical image segmentation simultaneity by means of priori-knowledge.

Agent environment is constructed two main agent types; Moderator agent and Local Agent. These agents have responsibility to segment the input image. Image processing task is all procedures that related to image to alter input image. There is no difference between local agent, autonomous agent, and agent, we use these terms alternatively. The global view of proposed method is shown in Figure 2. There is a moderator agent to create and initialize the local agents, after that each local agent commences its work. Moderator agent decides to create local agent in different part of image, or terminate the lifetime of special agent, if there is no progress for that agent. Also, after terminating the lifetime of all agents, moderator agent checks the all pixels in image were marked by local agents, if there are some unmarked pixels; moderator agent creates second generation of local agents in undiscovered area. The image was divided into several sub-images; each agent is located in center of its sub-image. First of all, an estimation of thresholding for each region within the image should be entered; this priori-knowledge can be derived from the other methods like our previous work [6].

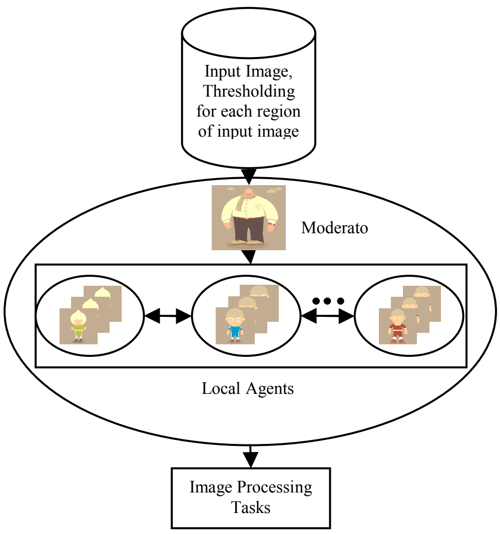

Figure 2. Global view of proposed method.

The Local agent starts by using an input image and minimum and maximum extreme thresholding values for each region which is given priori-knowledge. It tries to mark each pixel in sub-images by means of thresholding input. So each local agent marks each cell of sub-image individually and concurrently. In duration of marking procedure, each agent should make a decision about label of each pixel in sub-image; agent can do it by given priori-knowledge, but there are overlapped or gapped between given thresholding ranges of each region. In this situation, agent uses its properties to negotiate to the other agents. It means, if agent cannot find the type of a pixel, it negotiates to neighbour agent to find appropriate region type. But if no agent exists in neighbourhood of current agent, or neighbour agent has not knew proper information yet, agent leave that pixel as unmarked one for further processing of the other agents. Figure 3 shows all the behaviour of agents.

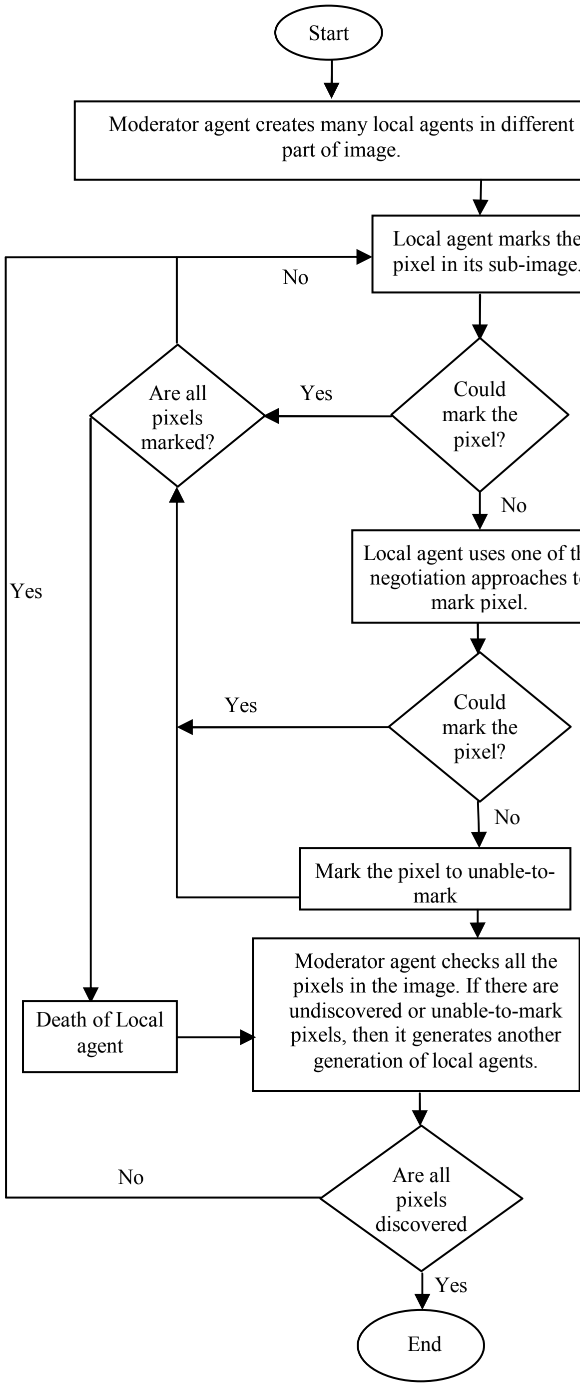

Figure 3. The Agents' behavior.

A local agent tries to find the appropriate label for the current pixel. If it cannot find the meaningful label, it goes to negotiate. The negotiation term is to calculate the mean value of the 3×3 window of the negotiable pixel. If this mean value is in the range of discovered thresholding, then the negotiable pixel can be marked by this mean value. The discovered thresholding means the thresholding range is not in the overlapped or gapped distance. The other approach for negotiation is to count the number of discovered neighbouring pixels.

The major type in the counting approach specifies the label of the negotiable pixel. For example, there are 8 pixels around the negotiable pixel. If there are 3 pixels labelled as region 1, 4 pixels labelled as region 2, and 1 pixel labelled as region 3. Then, the outcome from this approach is to mark the negotiable pixel as region 2 because majority of its neighbours were marked as region 2.

5. Experimental Results

In this section, we consider the experimental results of the proposed method qualitatively and quantitatively through image display and experiment measurements respectively.

The images used in the experiments are included two different CT sample images. In the first experiment, cranial CT images are acquired on a CT scanner with an image size 512×512, and a pixel size of $0.5mm\times0.5mm$. Upper human body CT images for the second experiment [8] are acquired on the same machine. The imaging protocol used is image size of 512×512, and a pixel size of $0.55mm\times0.55mm$.

As mentioned in section 5, each local agent through marked-pixel table can negotiate with other local agent. Therefore, the social ability, reactivity, and autonomy of the agent properties had been satisfied. However, we need to adjust the thresholding of each image, so some user interactions are necessary in this phase. Meanwhile some user interaction is required to find the exact thresholding range for each region globally. Predetermined parameter is not used through this phase. We have a global marked-pixel table which can be referred in experiment of other local agent.

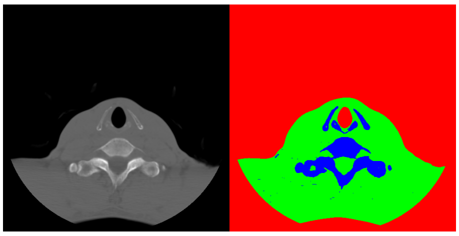

Image 1

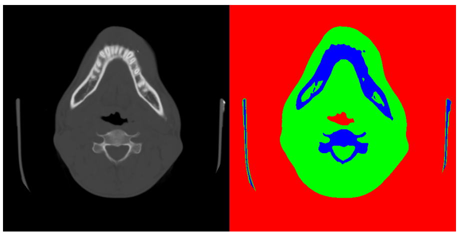

Image 2

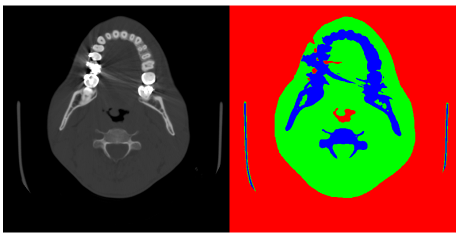

Image 3

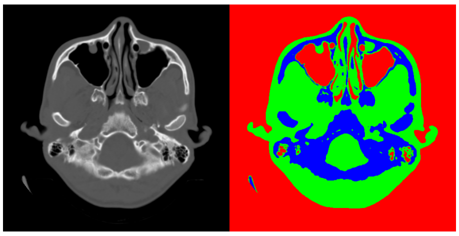

Image 4

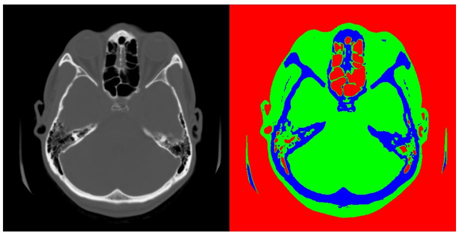

Image 5

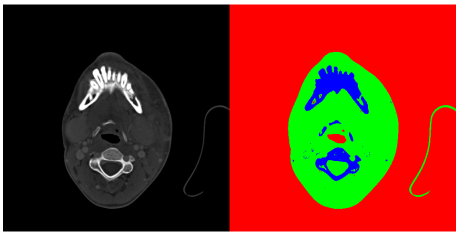

Image 6

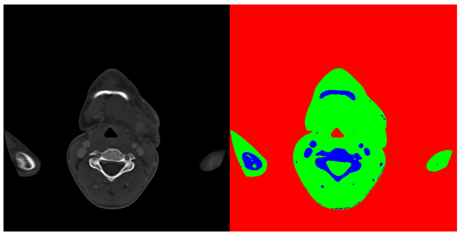

Image 7

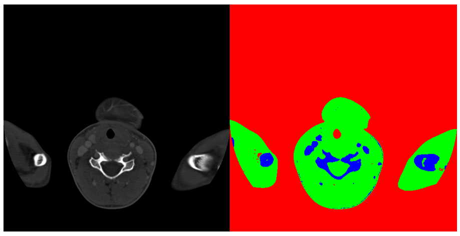

Image 8

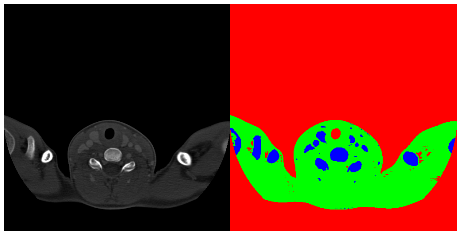

Image 9

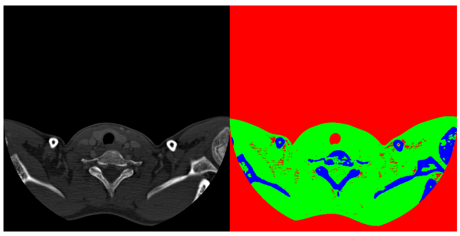

Image 10

Figure 4. The left images are original images and the right images are the segmented image after applying PMAM.

A subjective inspection discovered that in all experiments and in all data, the results are very close to the manually segmented images. Some examples are displayed in Figure 4. Quantitative segmentation evaluation has been used to assess segmentation methods [23]. The accuracy of a segmentation technique refers to how far actually segmented image is from the manually segmented image.

As a result, an appropriate segmented truth is needed for evaluation instead of a true delineation. In all experiments, all data sets have been manually segmented in the domain. For any image *C=(C, f)*, let C_d^M be the segmentation result which is obtained from *C*, and C_{td} is the true delineation. U_d is a binary image representation of a reference superset of pixels that is used to express the two measures as a fraction.

We used True Positive Volume Fraction (TPVF) and False Positive Volume Fraction (FPVF) from [20]. These equations are sufficient to describe the accuracy of the method:

$$TPVF_d^M = \frac{\left|C_d^M \cap C_{td}\right|}{\left|C_{td}\right|} \times 100 \tag{1}$$

$$FPVF_d^M = \frac{\left|C_d^M - C_{td}\right|}{\left|U_d - C_{td}\right|} \times 100 \tag{2}$$

The efficiency of segmentation method provides information on the sensible use of the proposed algorithm. Table 2 contains the mean computation time for each image. The proposed method is implemented on an Intel Core 2 Duo machine with a 2.00GHz CPU, and 2.00GB RAM. Also Table 3 lists the mean of TPVF and FPVF achieved in our experiment for each image in Figure 4.

Table 2. Efficiency of each image sample.

Data Set	Computation Time (Seconds)
Image 1	7
Image 2	7
Image 3	8
Image 4	7
Image 5	7
Image 6	7
Image 7	7
Image 8	7
Image 9	7
Image 10	8
Average	7

6. Discussion

We have Proposed a Multi-Agent Model (PMAM) to segment an image, by input of the maximum and the minimum gray-scale value of each region in image. In previous section, PMAM evaluated both qualitatively and quantitatively. The achieved average accuracy from PMAM is more than 91% in each region of the image. Also, the efficiency time is less than 8 seconds for all data sets. But, it's conceivable to improve result by some morphological operations.

Table 3. TPVF and FPVF for each image sample.

Data Set	TPVF (%)			FPVF (%)		
	BG	Skin	Bone	BG	Skin	Bone
Image 1	99.97	98.95	94.87	0.18	0.34	0.23
Image 2	98.54	97.57	91.94	0.67	1.35	0.87
Image 3	98.60	91.26	91.70	1.63	1.25	2.68
Image 4	99.40	95.91	91.86	0.00	1.95	1.32
Image 5	98.70	96.10	89.60	0.04	2.41	1.69
Image 6	98.41	91.61	98.17	1.9	0	0.43
Image 7	99.99	88.25	99.73	0.33	0.12	0.03
Image 8	100	82.82	99.07	0.41	0.49	0.08
Image 9	99.96	83.48	98.61	0.51	0.51	0.22
Image10	99.92	84.05	99.68	1.27	0.24	0.02
Average	99.349	91.00	95.523	0.694	0.866	0.757

Furthermore, the qualitative comparison shows interesting result, and better computation time. The proposed method is almost automatic. It requires a little adjustment on the result from a training method like one proposed in [5]. The most significant advantage is segmenting image to more than two regions in a parallel way. It means the interest regions can be more than one and with different characteristics. For example, the CT image of the cranial consists of three different regions, such as air, bone, and skin. PMAM segments the image into three different objects simultaneously. Also, the efficiency illustrates PMAM is applicable.

However, the qualitative result shows high accuracy of our proposed method; but the method has a few failings because of following reasons. First of all, PMAM is such a simple approach that can be used for images with less noise. When there is some noise or foreign object such tooth filling material in the CT image, the noise would be labelled as bone tissue instead of background or air, as shown at Image 3, Figure 4. Of course, it is possible to improve the method by putting more constraint in the model. For example, we can improve the social ability of each agent. In PMAM, the local agent uses the gray-scale value of neighbourhood pixels and the mean value of neighbourhood pixels for making decision to mark each pixel. This straightforward manner can be modified to a comprehensive one in future.

Finally, the adjustment of gray-scale value from a training method is a tedious work; the expert should consider the mean value of each low or high extreme for every region to conclude an appropriate gray-scale range.

7. Conclusions

In summary, we have shown that the proposed methods can be used to segment different anatomic structure in medical image as shown in Section 5. Our proposed method is almost automatic; it works without user interaction in segmenting the image. The most significant advantage of this method is segmenting image into more than two regions in a parallel way. It means the regions of interest can be more than one which the characteristics of each region are distinct.

The efficiency of this method illustrated in Table 2; that is significantly fast compared with other methods. The main results of this method are summarized below:

1. We attain significant result in segmentation accuracy; the average accuracy is more than 91% for each region in the images.
2. We achieve satisfactory result in computation time; the mean computation time of all datasets is less than 8 seconds.
3. We have the ability to segment simultaneously an image into some distinct regions.

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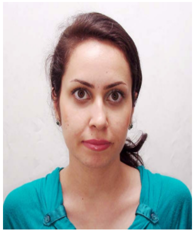

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