CHAPTER 4

SINGLE IMAGE SEGMENTATION USING METAHEURISTIC ALGORITHMS

4.1 INTRODUCTION

This chapter focuses on developing an automated segmentation system for brain tumor screening and diagnosis for digital MRI brain image applications. The main objective of the single image segmentation method is to increase the quality and efficiency of the CAD system which is used for detection of brain tumor. If the size of the tumor is smaller than 20mm and no metastasis is found, the chances of successful treatment is high. Therefore early detection of brain tumor is essential (Chen et al., 2008). In this chapter, single image segmentation by Markov Random Field - Maximum A Posteriori - Parallel Ant Colony Optimization (MRF-MAP-PACO) technique is developed and applied to high resolution digital MRI brain image with the aim of segmenting normal tissue from tumor tissue. The goal of the proposed work is to assist the radiologists in the decision making process and to augment their findings in order to accurately locate the tumor region. Figure 4.1 shows the steps involved in the single image segmentation process.

A segmented image provides a much simpler description of human brain from MRI and the pixel detection process is called image segmentation. Segmentation process identifies the attributes of pixels and defines the boundaries for pixels that belong to same group. Because of the importance of identifying objects from an image, there have been extensive research efforts on image segmentation in the past image segmentation methods. They are using fully automatic or semi-automatic approaches for medical imaging and other applications.

The design of the proposed segmentation method for the extraction of ROI from MRI brain image is critically based on two empirical assumptions as given below:

i. The distribution of pixel intensities within suspicious ROI is relatively normal and uniform.

ii. Suspicious areas are brighter than their immediate surrounding tissues.

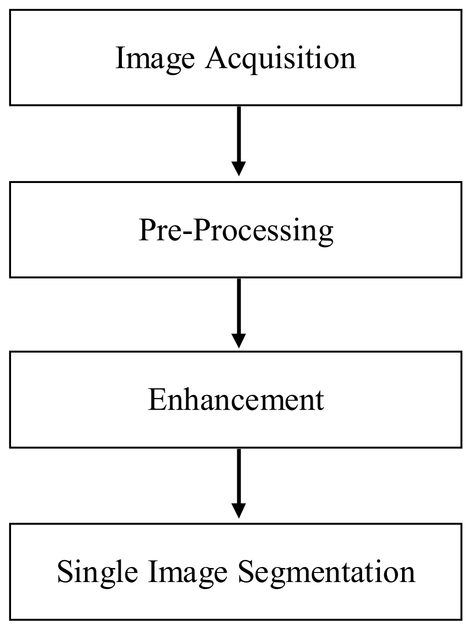

Figure 4.1 Steps Involved in the Single Image Segmentation Model

4.2 SINGLE IMAGE SEGMENTATION

Single image segmentation refers to the isolation of suspicious regions from MRI brain image. The task of optimizing the segmentation in digitized MRI brain image is investigated which is the crucial step in developing a well automated segmentation system. Segmentation depends on the accurate assessment of the tumor-normal tissue border as well as the information gathered from the tumor area.

The traditional segmentation methods are: Amplitude thresholding (Glasbey 1993 and Otsu 1979), Edge Detection (Kass et al., 1988), Region Growing (Kupinski and Giger 1998, Dubey et al., 2009 and Lu et al., 2003) and clustering (Li et al., 1993 and Hall et al., 1992) segmentation. These types of algorithms are used for dividing the brain images into three categories (a) Pixel Based (b) Region or Texture Based (c) Structural Based. Brigger et al., 2000 and Cohen et al., 1993 prescribed edge based segmentation for propagation of the labeled structures on the MRI. Edge based segmentation methods are based on the boundaries in the image. These techniques suffer from incorrect detection of boundaries owing to noise, over and under segmentation and variability in threshold selection in the edge image.

Yong Fan et al., 2001 designed semi-automatic segmentation method on volume tracking to estimate tumor volume. Hideki et al., 1990 specified a technique to partition the image space into meaningful regions. Yongyue Zhang et al., 2001 prescribed Markov random field model and EM model for segmenting stroke lesions on MRI multi sequences. Shan Shen et al., 2005 presented multi resolution Improved Fuzzy Clustering Method (IFCM) for segmenting the brain tissue structure from MRI. Hall et al., 1992 and Pham et al., 1999 segmented brain MR tumor images using an Artificial Neural Network (ANN). Zhou et al., 2005 described a Support Vector Machine (SVM) method to separate the target data from other boundary. Fletcher et al., 2001 designed alignment based feature segmentation of non-enhancing brain tumors. Thresholding is the simplest segmentation method where the classification of each pixel depends on its own information such as intensity and color. Thresholding methods are more efficient, only when the histograms of objects and background are clearly separated (Suzuki et al., 1991). Since the distribution of tissue intensities in MRI brain images is often very complex, these methods fail to achieve acceptable segmentation results.

Since the above mentioned methods are generally limited to relatively simple structures, clustering methods are utilized for complex pathology. Clustering is a method of grouping data with similar characteristics into larger units of analysis. Razaz M. 1993 described Fuzzy C-means (FCM) for segmentation purpose. Wells et al., 1996 introduced EM algorithm. In their method the intensity distribution of brain images is molded as a normal distribution which is untrue, especially for noisy images. The greatest shortcoming of clustering is it's over sensitivity to noise, as medical images contain significant amount of noise caused by operator, equipment and the environment. There is a compelling need for development of an efficient algorithm. In this work, single image segmentation by MRF- MAP-PACO technique is developed and applied to high resolution digitized MRI brain image.

4.2.1 Background Segmentation

Background segmentation of MRI refers to the separation of a brain image into two visually distinct regions namely the brain and the non -brain regions. This technique is also referred to as global segmentation. The precise segmentation of the brain region in MRI is an essential pre-processing step in the computerized analysis. Isolation of the brain region allows the search for abnormalities to be limited to the region of brain without influence from the background of the MRI. Hence background segmentation is the first step in pre-processing. This is achieved by applying image enhancement techniques, filtering and normalization. In this work, tracking algorithm removes the artifacts and the implemented ACWM filter enhances the MRI brain image.

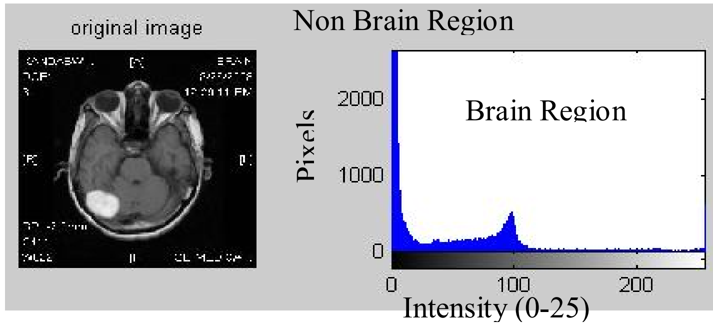

Figure 4.2 Intensity Histogram of MRI Brain Image

4.3 METAHEURISTIC ALGORITHMS

The medical image segmentation is an important step for analysis that can help in visualization, automatic feature detection, image-guided surgery, and also for registration of different images. Search techniques can be broadly classified as numerical or calculus based, enumerative, and guided random search. While the calculus-based methods assume the existence of derivatives and are also local in scope making their application severely restricted, the enumerative techniques fail when the size of the search space is large as in medical image segmentation. Guided search techniques are based on enumerative methods, but use additional information about the search space. These can be further divided into single-point search and multiple-point search, depending on whether it is searching just with one point or with several points at a time. The classical gradient search techniques perform efficiently when the problems under consideration satisfy tight constraints. But when the search space is discontinuous, noisy, high dimensional and multimodal, then heuristic related methods have been found to consistently outperform both the gradient descent method and various forms of random search.

Heuristic methods that are not bounded by the stringent restrictions of classical methods gain importance in such situations. In this regard, application of a search and optimization method that is capable of handling huge, complicated and multimodal search spaces is appropriate and natural (Bandyopadhyay 2007). Simulated annealing (Kirkpatrik 1983) is a popular single-point search technique based on the principles of statistical mechanics. Evolutionary algorithms like GAs, differential evolutions (Storn et al., 1997) Tabu search (Glover1989), Particle swarm optimization (Kennedy 1995), evolutionary and ant colony optimization (Dorigo et al., 1996) are popular examples of multipoint search, where a random choice is used as a tool to guide a highly explorative search through a coding of the parameter space.

4.4 SINGLE IMAGE SEGMENTATION USING ACO

ACO is a stochastic, recent population-based search technique that makes use of metaheuristics for problem solving. The first ACO was inspired by the studies of the social behavior of the real ants' colony and based upon their collective foraging behavior which is called as ant system (Dorigo 1997, and Deneubourg et al., 1983). In ACO each individual ant constructs a part of the solution using an artificial pheromone which reflects its experience accumulated while solving the problem and heuristic information depends on the problem (Bullnheimer et al., 1999). The new metaheuristic ACO has been receiving extensive attention owing to its successful applications to many combinatorial optimization problems. Like GA and simulated annealing approaches, the ACO also foster their solution strategy through the use of nature metaphors (Dorigo et al., 1996). Unlike simulated annealing or Tabu search in which a single agent is deployed for a single beam session, ACO and GA use multiple agents, each of which has its individual decision making based upon collective memory or knowledge (Azimi 2005). ACO optimizes the MAP probability (Thangavel et al., 2006). A labeling process consists of assigning the same label to the kernels having similar patterns (Kernel is a 3×3 window of neighborhood pixels).

4.4.1 Methodology

In ACO, real ants are capable of finding the shortest path from a food source to the nest without using visual cues. In many ant species, ants walking to and from a food source deposit a substance called Pheromone on the ground. Other ants perceive the presence of pheromone and tend to follow the paths where pheromone concentration is higher. Through this mechanism, ants are able to transport food to their nest in a remarkably effective way. Deneubourg et al., 1983 thoroughly investigated the pheromone laying and following behavior of ants; the higher the pheromone concentration found on a particular path, the higher is the probability to follow that path. This elementary behavior of real ants can be used to obtain optimum value from a population. The ACO algorithm is implemented to select the optimum label; only the pixels having this optimum label are extracted from the original brain image to form the segmented image.

4.4.2 Pheromone

Pheromone is a volatile chemical substance. Individual ants are simple insects with limited memory and capable of performing simple actions. However, the collective behavior of ants provides intelligent solutions to problems such as finding the shortest paths from the nest to a food source. The probability that an ant chooses a path increases with the number of ants choosing the path at previous times and with the strength of the pheromone concentration laid (Dorigo et al., 1997).

In this work, the labels created from the MRF method and the posterior energy function values for each pixel are stored in a solution matrix.

The goal of this method is to find out the optimum label value of the image that minimizes the MAP function value. Initially the value of number of iterations (N_i), number of ants (K) and the initial pheromone value (τ_0) are assigned.

4.4.3 Pheromone Initialization

The initial pheromone value τ_0 is initialized for each ant and a random pixel is chosen from the image which has not been selected previously. To find out whether the pixels are selected or not, a flag value is assigned for each pixel. Initially the flag value is assigned as 0. Once the pixel is selected the flag is changed to 1. This procedure is followed for all the ants. For each ant a separate column for pheromone and flag values are allocated in the solution matrix.

4.4.4 Local Pheromone Update

The pheromone values for all the randomly selected pixels are updated using Equation (4.1).

$$\tau_{new} = (1 - \rho) * \tau_{old} + \rho * \tau_0 \qquad (4.1)$$

where, τ_{old} and τ_{new} are the old and new pheromone values and ρ is rate of pheromone evaporation parameter in local update which ranges from zero to one ($0 < \rho < 1$).

Using Equation (4.2) the posteriori energy function U(x) or Fitness Value (FV) can be calculated for all the selected pixels from the solution matrix.

$$U(x) = \min \{\Sigma[(y_i-\mu_i)^2/(2*\sigma_i^2)]+\Sigma \log(\sigma_i)+\Sigma V(x_i)\} \qquad (4.2)$$

where,

y -Intensity value of pixels in the kernel.

μ - Mean value of the kernel.

σ - Standard deviation of the kernel,

V - Potential function of the kernel and

x - Center pixel of the label.

$$V(x) = \begin{cases} \beta, & x_1 = x_2 \text{ in the kernel.} \\ 0, & \text{otherwise} \end{cases}$$

where, β is visibility relative parameter ($\beta \geq 0$).

4.4.5 Global Pheromone Update

The posteriori energy function value for all the randomly selected pixels from each ant is compared to select the minimum value from the set which is known as 'Local Minimum' (L_{min}) or 'iteration's best solution.

4.5 PROPOSED MRF-MAP-PACO TECHNIQUE FOR SINGLE IMAGE SEGMENTATION

PACO is a parallel implementation of ACO where ants do their work simultaneously on different processing units. This intuitively provides improved performance and speeds up the searching process by exchanging information about the solutions they find.

Stutzle et al., 1999 described the simplest case of parallelization where the entire searches can be performed concurrently. Michel and Middendorf 1998 discussed exchanging information where separate ant colonies exchange trail information pheromone matrices. Chen et al., 2008 proposed a strategy for improving the performance of PACO by avoiding early convergence. Liu et al., 2005 presented PACO based on construction graph decomposition which has computation complexity. Lin et al., 2004 reduced the computational complexity by dividing the problem into sub components corresponding to two solution vectors. Ahamed Sames et al., 2010 used PACO for traveling sales man problem. Bin Yu et al., 2005 used coarse grain PACO for optimizing bus transit network.

In this proposed MRF-MAP-PACO, master-slave and information exchange approaches are combined to improve the result of image segmentation. MRF-MAP is used as the fitness function in this work. Fitness function calculates the posteriori energy function and the proposed approach seeks the pixel point where the posteriori energy value is less. The suspicious region is segmented using MRF-MAP-PACO and performance evaluations are analyzed.

MRF-MAP-PACO independently executes the sequential algorithm on M-1 parallel sub colonies. Parallel runs have no communication overhead. They are useful in randomized algorithms. In case of parallel independent runs, the best solution of the M runs is taken as the final solution.

To speed up the searching process, the master-slave approach is introduced in the proposed work. One master colony is used to update the main data structures for the ACO algorithm, constructing initial solutions for the local search algorithms and sending the solutions to other sub colonies which improve them by local search. The master collects these locally optimal solutions and in case a sufficient number of such solutions have been arrived at, it updates the trail matrix before constructing more solutions.

The master is responsible only for spawning the slaves and prunes them whenever a slave returns the optimal solution to the master. In all the processing, the local search and the pheromone matrix update are done by the slaves. Slaves also exchange solutions independently from the master to decrease the overhead of the communication with the master. The master spawns a number of slaves and each slave finds the best solution and sends it back to the master. During this operation, each slave periodically exchanges information with its neighbor. Each slave uses this information to update its pheromone matrix. The best solution is determined by the iteration length. Each sub-colony chooses the iteration with the minimum length as the best and reports it to the master program at the end of its search. The master program finds the best solution it received from its slaves and presents this as the proposed solution.

In this approach, each colony is given a valid IDs and they select their partners so that the slaves with even IDs exchange their information with their successors and those with odd IDs exchange their local optimal with their predecessors. Therefore, each colony exchanges information with the same colony at the end of each time interval. Slaves exchange three parameters: their pheromone matrices, the iteration length and the best iteration obtained so far. For each colony, the best ant represents its sub colony and its best iteration and length are sent to its partner colony. Whenever the master receives the optimal solution, it multicasts to all slaves that this solution has been found and the slaves consequently prune themselves. This reduces the time wasted in other slaves who would not know otherwise that another slave has found the optimal solution.

The fundamental principle of MRF-MAP- PACO is to divide K ants into M sub colonies, so that the number of ants per each sub ant colony is the total number of ants divided by the number of sub colonies. In the algorithm designing, each colony is treated as an independent processor and then the ant colony can search the best solution independently. In order to avoid the local optimization in some colonies when the ant is doing the job, the other sub colonies should carry out the information exchange with each other in the chosen fixed time interval condition.

4. 5.1 Modifications in ACO

In ACO each individual ant constructs a part of the solution using an artificial pheromone which reflects its experience accumulated while solving the problem. But in the proposed MRF-MAP-PACO approach, totally M colonies are considered in which M-1 colonies are treated as slaves and one colony is assigned for master. Each colonies visit all the pixels without revisit. Initially, the pheromone value for all the colonies is initialized and the posterior energy values are computed. Finally each slave colony yields global optimum value and the master colony system also yields global optimum value. Therefore M-1 slave colonies produce M-1 optimum values. These values are compared and the highest global optimum value from slave colonies is computed and compared with the master global value. If the values of the slave colonies are less than the master value then the values are discarded otherwise the values are interchanged or swapped. This optimum value is treated as adaptive threshold value. In the MRI image, the pixels having lower intensity values than the threshold value are changed to zero. The entire procedure is repeated for number of times to obtain the more accurate value.

The time taken to find the optimal solution using MRF-MAP-PACO is much shorter than that of using the sequential ACO. The sequential ACO runs M tries on a single colony whereas MRF-MAP-PACO runs single try on M colonies.

4.5.2 Functions of Master Colony in MRF-MAP- PACO

(i) Initialize number of processes N_p.

(ii) Spawn N_p processes.

(iii) Multicast to all slave processes N_p and the task IDs of all slaves.

(iv) Send a number between 0 and N_p that identifies the task inside the program till all slaves send back solution.

(v) If a slave returns an optimum solution which is better than any solution received before, multicast this iteration length to all the slaves.

4.5.3 Functions of Slave Colony in MRF-MAP-PACO

(i) Get N_p and task IDs of all slaves from the master.

(ii) Initialize pheromone matrix. (The matrix which contains the values of control parameters or solution variables is called as pheromone matrix).

iii) For each try, check the reach ability of termination condition (maximum allowed time and optimal solution found). If the master received a new optimal solution, prune this slave and update pheromone matrix.

(iv) Identify neighbor for information exchange and send to neighbor the best tour found, its length and the pheromone matrix.

(v) Update pheromone matrix using information received from neighbor.

(vi) Send to master the best solution found.

4.5.4 Algorithm for Single Image Segmentation by MRF-MAP-PACO

(i) Read the MRI brain image to M_{ij}.

(ii) Assign ROI pixels in M_{ij} to B_{ij}.

(iii) Divide the image to kernel of 3x3 sub images to G.

(iv) Calculate fitness function U (x) using (4.2).

(iv) Store U(x) in separate matrix S.

(v) Assign values to number of iterations (N_i), number of ants (K) and initial pheromone value (τ_0) and evaporation parameter ρ and the flag.

[Here, N_i =20, K=10, τ_0=0.001 ρ=0.9 and flag=0]. If flag value = 0, pixels are not selected yet else selected already.

(vi) Create a solution matrix (S) to store the labels and posterior energy values of all the pixels.

(vii) Select a random pixel for each ant which is not selected already.

(viii) Update the pheromone values using (4.1).

(ix) Select the minimum value from the set and assign as local minimum (L_{min}).

(x) Compare L_{min} with the global minimum (G_{min}).

If $L_{min} < G_{min}$, assign $G_{min} = L_{min}$.

(xi) Select the ant, whose solution is equal to L_{min}, to update its pheromone globally.

(xii) Perform the steps (vii) to (ix) till all the image pixels are selected.

(xiii) If G_{min} is the kernel's best minimum, then the co-ordinates of the pixels from G_{min} can be considered as ROI.

In the MRI brain image, the pixels having intensity values lower than the threshold value are changed to zero. The entire procedure is repeated for M-1 slave colonies to obtain the more accurate value.

Figure 4.3 and 4.7 shows the screenshot of single image segmentation.

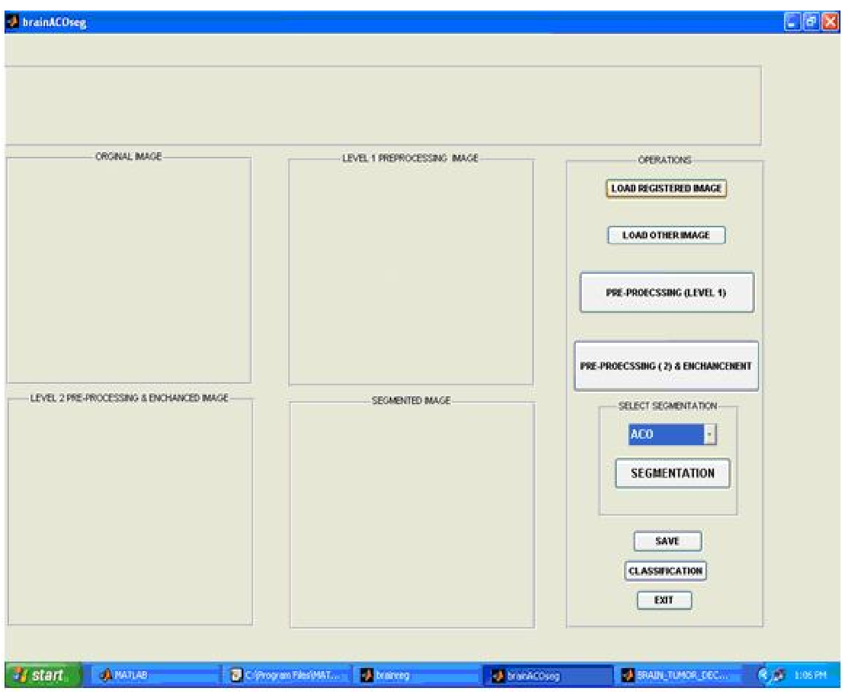

Figure 4.3 Screenshot of Initial Stages of MRF-MAP-PACO Segmentation

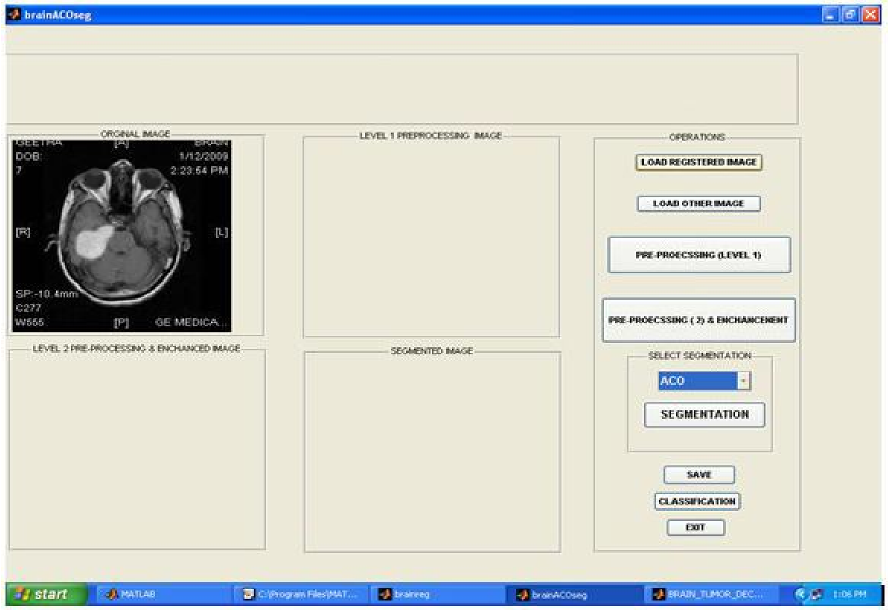

Figure 4.4 Screenshot of Image Acquisition of Target Image Corresponding MRF-MAP-PACO Segmentation

Figure 4.5 Screenshot of Pre-processing of Target Image Corresponding MRF-MAP-PACO Segmentation

Figure 4.6 Screenshot of Enhancement of Target Image Corresponding MRF-MAP-PACO Segmentation

Figure 4.7 Screenshot of Segmented Image Corresponding MRF-MAP-PACO Segmentation

4.6 PERFORMANCE EVALUATION FOR SINGLE IMAGE SEGMENTATION

The success of the proposed technique is determined by the extent the potential abnormalities can be extracted from the corresponding MRI brain images based on analysis of the image segmentation. Segmentation of tumor in MRI brain image is a demanding task, especially in the early stage, because the size of the tumor is very small, having low contrast value embedded in a non uniform background with significant spatial high frequency components. Once the ROI is found, it is easier to proceed with the analysis because the tumor presence within the ROI has distinguishing characteristics to be classified as tumor. However, the detection of ROI is a harder task because most of the tumors exhibit poor image contrast and may be highly connected to the surrounding normal tissues which are simplified by segmentation process. The performance metric of the proposed single image segmentation technique is validated in terms of the validation parameters such as the adaptive threshold value, number of segmented pixels, execution time to find the optimum value and the detection rate. Figure 4.8- 4.10 describes the performance of the proposed system.

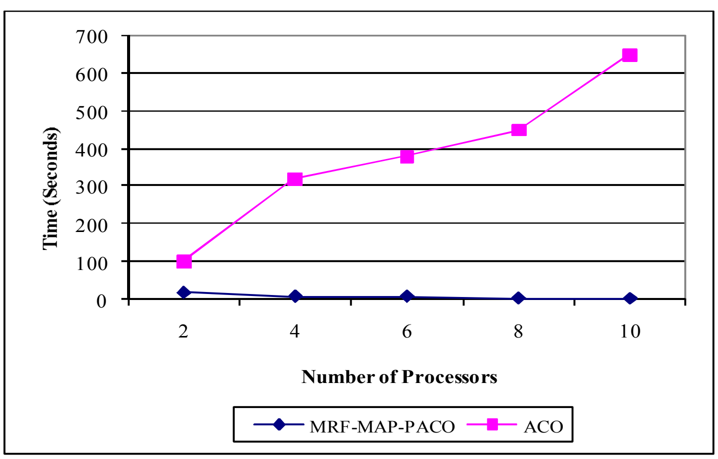

Figure 4.8 Comparison between ACO and MRF-MAP-PACO to Find Optimum Solution

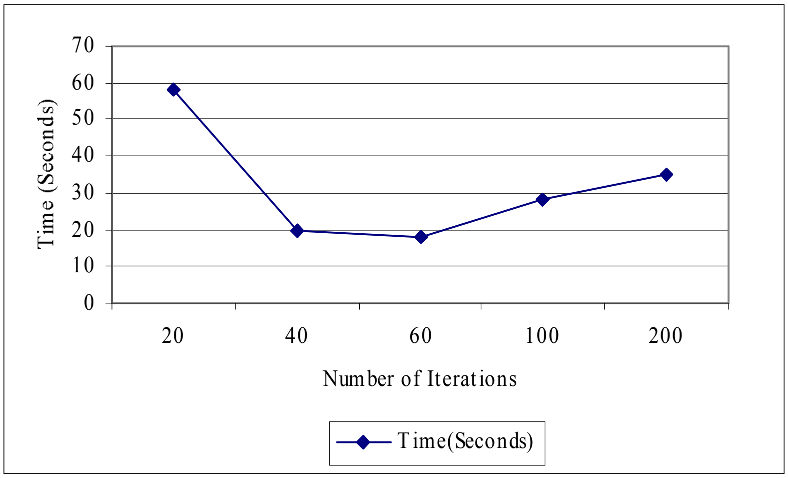

Figure 4.9 Time to Find Optimum Solution by Each Iterations

Figure 4.9 demonstrates that the time taken to find the optimum solution using MRF-MAP-PACO is much shorter than the ACO. Since MRF-MAP-PACO runs 1 try on M processors where as ACO runs M tries on a single processor. Figure 4.9 shows the effect of the increase in the number of processors to find the optimum solution. For example with 6 processors, the time taken to find the optimal solution is 376 sec by ACO technique whereas it is 8.03 seconds by MRF-MAP-PACO technique which is comparatively very low. As the number of processor increases, the chances that one of them gets fortunate and finds the optimum solution sooner increases. Unlike ACO, MRF-MAP-PACO runs each number of processors several times and the average time has been plotted in the graph. Information exchange is kept disabled when taking these measures. Figure 4.9 describes that as the number of iterations increases from 60 to 200, the time taken to find the optimum solution increases since the benefit gained from information exchange with the neighbors decreases. In addition, as the iteration decreases from 40 to 20, the time taken to find the optimum solution increases. This is because of two factors: i) As the iterations decreases, the overhead of communication between the slaves becomes too high that it overweighs the benefit gained from information exchange. ii) When the iteration is too short, the processor may not have enough meaningful pheromone distribution that its partner can benefit from and there would be no significant difference in the pheromone distribution from one interval to the next. The methods which use T1weighted brain images are compared with the proposed method. The performance analysis is explained in the below table 4.1.

Table 4.1 Comparative Performance Analysis of Single Image Segmentation

Method	Author	Detection Rate (%)
FCM with GA	Yingli Zhang et al., 2007	90.26
Modified FCM	Lin et al., 2004	88.73
IFCM with GA	Shan shen et al., 2005	92.00
ACO	Myung-Eun Lee et al., 2009	91.23
RB-HMM	Huang et al., 2010	92.99
Proposed MRF-MAP-PACO		96.59

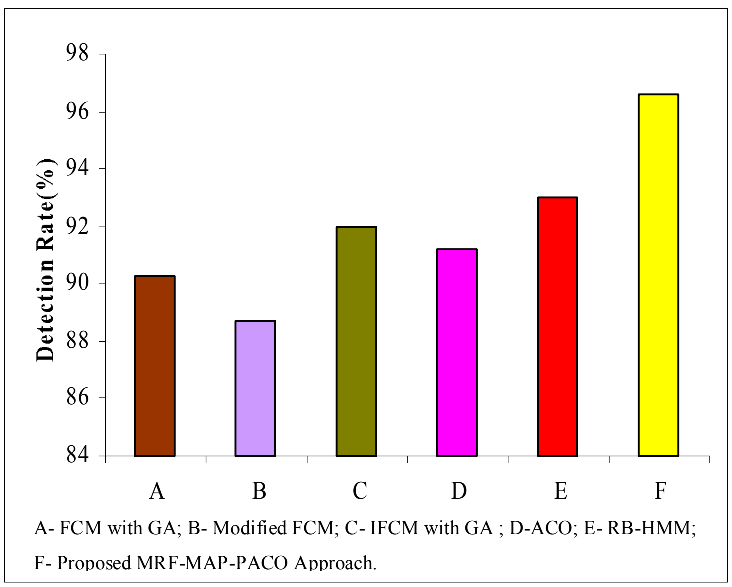

Figure 4.10 Comparative Performance Analysis of Single Image Segmentation with Existing Approaches in terms of Detection Rate

In FCM the membership value measures the difference between the intensity of pixels and the cluster center, and has no resistance to noise. Although many extended algorithms based on FCM have been developed to overcome this shortcoming, none of them are flawless since one pixel is too small to represent the part of the image. In addition the FCM based methods have the inherent disadvantage in segmentation accuracy because of the non-global optimum searching ability. Therefore the segmentation results will be often trapped in the local optimum. To overcome this problem, the proposed approach assumes that an attraction exists between the neighboring pixels and hence each pixel attempts to attract its neighboring pixels towards the findings of global optimum search. If a pixel has a very similar intensity to one of its neighbors, the attraction between them should be stronger than the attraction between the pixel and another neighbor with rather different intensities. In addition to the global optimum value the proposed approach performs the segmentation using parallel master-slave approach and it detects the tumor with better detection rate of 96.59% which is much improved while compared with the other existing segmentation techniques.

From the Figure 4.10, it is evident that the method developed and presented in this report has achieved the detection rate value of 96.59% compared to the value of 90.26% by FCM with GA technique (Yingli Zhang et al., 2007), 88.73% by Modified FCM technique (Lin et al., 2004), 91.23% by ACO (Myung-Eun Lee et al., 2009, 92% by IFCM method (Shan shen et al., 2005) and 92.99% by RB-HMM method (Huang et al., 2010).

Based on the analysis presented in this chapter, the paper entitled "Implementation of Computer Aided Diagnosis System Based on Parallel Approach of Ant Based Medical Image Segmentation", in the Journal of Computer Science, Vol.7, No.2, pp.291-297, 2011. (ISSN: 1549-3636).

4.7 CONCLUSION

The main objective of the segmentation process is to increase the quality and efficiency of the segmentation techniques in CAD system which is used for detection of brain tumor. In this work, image segmentation by MRF-MAP- PACO method is developed and applied to MRI brain image aiming at segmenting normal tissue from tumor tissue. Besides, the work investigates with the task of optimizing the approach for image segmentation in digitized MRI brain image.

The goal of the proposed work is to assist the radiologists in the decision making process and to augment their findings in order to accurately locate the tumor region at the early stage. The proposed MRF-MAP-PACO segmentation algorithm provides a significant enhancement for the MRI brain image segmentation. It outperforms the existing segmentation techniques in terms of less number of segmented pixels 1026 with low threshold value of 120 at very less execution time of 10-30 seconds in segmenting tumor pixels. The adapted method does not suffer from the nesting problem which presents in the existing techniques. The proposed MRF-MAP-PACO has achieved the improved detection rate of 96.59% which is 20% more compared with the other segmentation techniques. The advantage of the proposed approach is that it eliminates the influence of noise in segmentation. It has achieved great execution speed of 10-30 seconds. The visual assessment has also confirmed the findings through experiments on MRI brain images. The observations made in this chapter have also been summarized in the paper published.