Brain Tumor Segmentation using Swarm Intelligence Approach

Tinali Kamble, Prachi Rane

Abstract— Segmentation is an important step in medical image analysis which is used to extract the boundary of an area we are interested in. Swarm intelligence is an emerging area in the field of optimization and researchers have developed various algorithms by modeling the behaviors of different swarm of animals and insects such as ants, termites, bees, birds, fishes. Inspirations from swarm intelligence have been used in recent years in the field of Image processing problems. Optimization algorithms based on swarm intelligence are multi-agent, robust and resilient approaches, which are inspired by intelligent attributes of swarms. Their main advantage is the simple agents in communication which are capable of solving complex problems. With the aid of swarm intelligence, it is possible to create computer simulations of biological concepts. In this paper Ant Colony Optimization (ACO) is used for Brain Tumor Segmentation from Magnetic resonance imaging (MRI). Ant Colony Optimization (ACO) is a branch of Swarm Intelligence; ACO is new meta-heuristics algorithm in the field of image segmentation, which is inspired by behavior of real ants.

Index Terms— ACO, Brain Tumor, Magnetic resonance Imaging, Segmentation, Swarm intelligence.

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1 INTRODUCTION

Brain is the portion of central nervous system that is located within the skull. It is soft spongy mass of tissues that is protected by bones of skull and three thin membranes called meninges. A brain tumor is an abnormal growth of tissue in the brain. Unlike other tumors, brain tumors spread by local extension and rarely metastasize (spread) outside the brain. Brain Tumors can be either benign, meaning non-cancerous, or malignant, meaning they may be cancerous. It is estimated that between 30000 and 35000 new cases of primary brain tumors (PBT) will be diagnosed in the upcoming year in the USA (1-2 percent of newly diagnosed cancers overall) [1]. In India near about 80,271 people are affected by various type of tumor (2007 estimates). Brain tumor segmentation in Magnetic Resonance Imaging (MRI) is a complex problem in the field of medical imaging. Swarm intelligence is an emerging area in the field of optimization and researchers have developed various algorithms by modeling the behaviors of different swarm of animals and insects such as ants, termites, bees, birds, fishes. With the aid of swarm intelligence, it is possible to create computer simulations of biological concepts. Reliable segmentation in magnetic resonance imaging is of great importance for surgical planning and therapy assessing.

2 REVIEW OF RELATED WORKS

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Majority of the research in medical image segmentation pertains to its use for MR images, particularly in Brain imaging because magnetic resonance imaging having high resolution and gives detailed imaging. Clark M C [2], proposed hybrid approach combining knowledge based techniques with unsupervised fuzzy clustering to detect tumor abnormalities and completely label normal volumes. Each slice within an input Volume is processed separately using the fuzzy c- means algorithm to initially segment MRI data into ten classes or region. These regions have much better semantic meanings in MR brain images than edges and knowledgebased analysis can be effectively applied for classification and labeling purpose. Fuzzy clustering using Fuzzy C- Means (FCM) algorithm proved to be superior over the other clustering approaches in terms of segmentation efficiency. But the major drawback of the FCM algorithm is the huge computational time required for convergence. Yongyue zang proposed a hidden Markov random field model and Expectationmaximization algorithm for segmentation of brain tumor in MRI [3]. This method is based on estimation of threshold that is heuristics in nature thus most of the time this method does not gives the accurate result it is also computationally very expensive. Bin Li proposed membership constraints FCM algorithm by incorporating spatial information for image segmentation [4], as conventional FCM algorithm does not take into account the spatial information of image. The proposed algorithm overcome the disadvantages of conventional FCM algorithm band gives improved result than that of conventional FCM algorithm for MR images on different noise level. T. bala ganesan proposed fuzzy clustering method along with wavelet coefficient method for segmentation and classification

Tinali Kamble is currently pursuing masters degree program in electronics engineering in G.H. Raisoni College of Engineering, India.E-mail: tinalikam_2008@rediffmail.com

Prachi Rane is currently working as Assistant professor in electronics engineering in G.H. Raisoni College of Engineering, India. E-mail: ashabhandvale@gmail.com

of tumor in MRI; here they also used silhouette method to measure the strength of clustering [5]. M masroor Ahmed and bin mohamad used K-means clustering method for grouping tissues and perona-malik Anistropic Diffusion model for image enhancement [6], this method gives good result for segmentation. Ping Wang used FCM algorithm by modifying memberships weighting of every cluster and integrating spatial information [7], this method gives good result for MR images of different noise type. Sriparna saha proposed fuzzy symmetry based genetic clustering technique [8], here number of cluster are evolved by variable length genetic fuzzy clustering technique. For measuring quality of cluster fuzzy Point symmetry based cluster validity index is proposed. This technique performs better than FCM and Expectationmaximization algorithm but this technique does not consider spatial information and sometime gives poor segmentation. This technique does not work properly for data set which has same point as a center for different cluster. Saif D. Salman proposed Watershed Transformation Method [9] used to separate abnormal tissue for normal surrounding to get real identification of involve and noninvolved area that helps the Surgeon to distinguish involved area precisely; however there is problem of over segmentation of images. Mirajkar G. proposed new algorithm for segmentation of tumor from MRI [10], Here Gabor wavelets are applied to the approximation images and capture the tumor characteristics at all level of decomposition but the disadvantage of this method is that computation time required for feature extraction is quite high which limits the retrieval speed. T Logeshwari proposed the HOSM method [11] is the combination of self organization map and graphics mapping technique, there are two processes involved in vector quantization one is training process which determine the set of codebook according to probability of input data and other is encoding process. Main drawback of this method is that, number of neural network in competitive layer needs to be approximately equal to the number of region desired in segmented image. Manoj K Kowar proposed Histogram thresholding technique for brain tumor detection and segmentation in MRI [12]. This method is based on threshold value; here key is to select the threshold value. But problem with this method is that it does not work well for an image without any obvious peaks or with broad of flat valley; and does not consider spatial details so cannot guarantee that segmented region is contiguous.

3 PROPOSED METHOD

3.1 Ant Colony Optimization (ACO)

The Ant colony optimization Algorithm (ACO) [13], [14], [15], is a Probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs. It is initially proposed by Marco Dorigo in 1992 in his PhD thesis. Ant colony optimization (ACO) is a nature-inspired optimization algorithm that is motivated by the natural foraging behavior of ant species. In ACO, a colony of simple agents, called artificial ants, search for good solutions at every generation. Every artificial ant of a generation builds up a solution step by step. These ants, once build a solution, will evaluate the partial solution and deposit some amount of pheromone to mark their paths. The following ants of the next generation are attracted by the pheromone so that they will likely search in these areas nearby.

3.2 Segmentation of Brain tumor using ACO

3.2.1 Image Acquisition

Images of a patient obtained by MRI scan is displayed as an array of pixels (a two dimensional unit based on the matrix size and the field of view) and stored in Matlab 7.10.0. All the test images were converted to grayscale images; grayscale image is an image which is composed exclusively of shades of gray, varying from black at the weakest intensity to white at the strongest. Each grayscale image resized to the size of 256x256.

3.2.2 Pre-Processing

In medical image processing and especially in tumor segmentation task it is very important to pre-process the image so that segmentation algorithms work correctly. pre-processing of MRI includes removal of noise in images.MRI images may contain salt-and-pepper noise, median filter is more effective in removal of this type of noise from MRI ,so that images can be made more suitable for further processing.

3.2.2.1 Median filter

The median filter is a popular nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing. Median filtering is very widely used in digital image processing because under certain conditions, it preserves edges while removing noise [16]. Sometimes known as a rank filter, this spatial filter suppresses isolated noise by replacing each pixel's intensity by the median of the intensities of the pixels in its neighborhood. It is widely used in de-noising and image smoothing applications. Median filters exhibit edgepreserving characteristics, which is very desirable for many image processing applications as edges contain important information for segmenting, labeling and preserving detail in International Journal of Scientific & Engineering Research, Volume 4, Issue 5, May-2013 ISSN 2229-5518

images. This filter may be represented by equation (1):

$$G(u,v) = median\{I(x, y), (x, y) \in wF\}$$
(1)

Where,

wF = w x w Filter window with pixel (u, v) as its middle

3.2.3 Steps Involve in ACO for tumor segmentation in MRI

Algorithm consists of following steps;

3.2.3.1 Pheromone Initialization:

The initial pheromone value T0 has been initialized for each ant and a random pixel is chosen from the image, which has not been selected previously. To find out the pixels is been selected or not, a flag value is assigned for each pixel. Initially the flag value is assigned as 0; once the pixel is selected 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.

After each construction process, the pheromone values are updated. It Perform Two Pheromone update Process;

3.2.3.1.1 Local Pheromone Update Process:

Each time an ant visits a pixel, it immediately performs a local Pheromone update on the associated pheromone according to the equation (2):

$$T_{new} = (1-\rho). T_{old} + \rho. T_0$$
 (2)

3.2.3.1.2 Global Pheromone Update Process:

After all the ants finish the construction process, global pheromone update is performed on pixels that have been visited by at least one ant. The global pheromone update is performed only on the best-so-far solution according to the equation (3):

$$T_{\text{new1}} = (1-\rho). \text{ Told} + \rho. \Delta \text{Told}$$
(3)

Where, T_{new} and T_{old} are the old and new pheromone values, and ρ is rate of pheromone evaporation parameter, ranges from [0, 1] i.e., $0 < \rho < 1$. Labeling is performed for the unique region obtained from ACO. Labeled region having similar pheromone value, calculating the mean of neighborhood 3x3, After calculating the mean values Select the maximum value of mean for tumor detection. Then Segmenting the image from pheromone using the threshold value, here Choose threshold is approximately 60 percent of maximum mean value.

4 RESULT

Firstly the MRI data is taken as input. We have taken 20 MRI images for testing. Proposed algorithm uses 50 numbers of iteration and 100 construction steps. Results obtained using ACO for Brain tumor segmentation in MRI is shown below;

Original Image	Segmented Image
1(a)	1(b)
.1: (a) original image	(b) segmented image

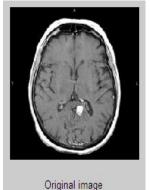


Fig.

Onginar image

2(a)

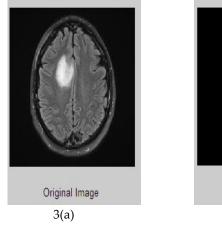
Fig.2: (a) original image

Segmented Image

2(b)

(b) segmented image







3(b)

Fig.3: (a) original image

(b) segmented image

5 CONCLUSION

In this paper, we have presented Swarm Intelligence approach for detection of brain tumor. Furthermore we have also discussed previous work carried on Brain tumor detection and Segmentation in MRI. With this proposed Ant colony Optimization algorithm it is possible to accurately segment the tumor portion from MRI. The simulation results shows that the proposed approach gives efficient results for Brain tumor segmentation in MRI. The proposed Work for tumor Segmentation can further be extended for classification of Brain tumor with the help of Artificial Neural network

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