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An Assessment on Automatic Brain Tumor Detection

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Abstract— Segmentation of organisational segments of the brain is the essential problem in medical image investigation. This paper reviews several existing brain tumor segmentation and detection methodology for MRI of brain image. Altogether the phases for detecting brain tumor have been discussed comprising pre-processing steps. Pre-processing involves several operations like non local, diagnostic correction methods; Markov random field methods and wavelet based methods have been discussed

Keywords— Analytic Correction, Brain Tumor Segmentation, Cerebrospinal fluid, MRI, Markov Random Field

I. INTRODUCTION

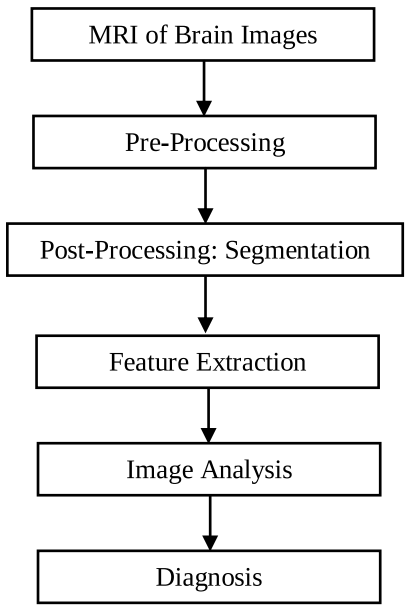
A brain tumor is a mass of abnormal cells budding in the brain. Primary brain tumors are those that initiate in the brain and be likely to to stay in the brain. Metastatic brain tumors begin as a cancer elsewhere in the body and migrate, to the brain. There are further than 120 different types of brain tumors; some are malignant (cancer), rest are nonthreatening or benign which are usually noncancerous. The basis of brain tumors is unknown. Benign or malignant, primary or metastatic, brain tumors can be treated. Added knowledge about brain tumors has been gained in the last ten years than in the past hundred years due to involvement of high resolution techniques like functional MRI (fMRI), Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Single Photon Emission Computed Tomography (SPECT) and Positron Emission Tomography (PET) in medical imaging. Imaging practices to diagnose, stage, and follow patients with brain tumors are central to the clinical management. MRI is among the most universally used technique for lesion detection, definition of extent, revealing of spread and in evaluation of either enduring or recurring disease.

Magnetic Resonance Imaging has become a far and wide used method of high quality medical imaging. Magnetic resonance imaging (MRI) is a progressive medical imaging technique providing rich information about the human soft tissue anatomy. The aim of magnetic resonance (MR) image segmentation is to accurately identify the principal tissue structures in these image volumes. Segmentation is a process of partitioning an image space into some non-overlapping meaningful homogeneous regions or objects. The success of an image analysis system depends on the quality of segmentation. In the analysis of medicinal imageries for computer assisted conclusion and therapy, segmentation is often required as a preliminary stage. Tumor segmentation from MRI data is a predominantly puzzling and time consuming task. Because the boundaries of different tissues in MRI brain images are not clear and the intensities of the white and gray matter are very close. Many methods have been projected for MRI brain tissue segmentation recently. Although improving imaging techniques (e.g., contrast agents, biological markers) should expedite the segmentation process, medical images are relatively difficult to segment for several unwanted stuffs like low signal-to-noise and contrast-to-noise ratios and multiple and discontinuous edges. Tumors have a large multiplicity in shape and look with intensities overlapping the normal brain tissues. In addition, a growing tumor can also repel and deform nearby tissue.

The procedure of segmenting tumors in MR images as contrasting to natural scenes is particularly challenging. The tumors fluctuate prominently in size and position, have a variety of shape and appearance properties, have intensities overlapping with normal brain tissue, and time and again a getting bigger tumor can deflect and deform nearby structures in the brain giving an abnormal geometry also for healthy soft tissue. For that reason, in general it is difficult to segment a tumor by simple unsupervised thresholding. Alternatively, different machine learning (ML) classification techniques have been explored: SVMs (Support Vector Machines), MRFs (Markov Random Fields), and most recently CRFs (Conditional Random Fields). Apart from the work on classification techniques, recently discrete segmentation approaches using graph cuts have been proposed for brain tumor segmentation. On the other hand among the continuous approaches, the variation and level set methods have also been explored with considerable interest in the past few years [1]. Therefore, it is indispensable to develop set of rules to obtain robust image segmentation such that the following may be observed:

- Automatic and semi-automatic demarcation of areas to be exposed to radio-surgery.
- Outlining of tumors before and after surgical or radio-surgical intervention.
- Tissue grouping: Dimensions of white matter (WM), Grey matter (GM), Cerebrospinal fluid (CSF), Skull, Scalp and abnormal tissues.

II. GENERAL METHOD OF BRAIN TUMOR DETECTION



A medical image may be distinct as a two-dimensional smooth function, f (x, y) where x and y are spatial (plane) coordinates, and the breadth of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When (x, y) and the breadth values of f are all finite, discrete quantities, we call the image a digital image. The arena of digital image processing discusses to processing digital images by means of a digital computer. Note that a digitized medical image is collection of a finite number of elements, each of which has a particular position and value. These elements are stated to as picture elements or pixels.

Pre-Processing

Pre-processing primarily implicates those operations that are normally necessarily prior to the main goal analysis and abstraction of the desired statistics and normally geometric corrections of the original actual image. These improvements include rectifying the data for irregularities and undesirable atmospheric noise, removal of non-brain element image and translating the data so that they correctly reproduce in the original image. Segmentation is the process of partitioning an image to quite a lot of segments but the main technical hitches in segmenting an images are i) Noise, ii) Blur Low Contrast, iii) The bias field (the existence of smoothly varying intensities inside tissues) , iv) The partial-volume effect (a voxel adds in multiple tissue types). Image filtering and enhancement stage is the most obvious part of medical image processing. This pre-processing phase is used for reducing image noise, highlighting important portions, or displaying obvious portions of digital images [2]. Some more techniques can employ medical image processing of coherent echo signals preceding to image generation and some of the images are dangling from clip hence they may produce noise. The enhancement stage includes resolution enrichment; contrast augmentation. These are used to suppress noise and imaging of spectral parameters.

Image Segmentation Approach

There are more than a few types of segmentation possible to segment a tumor from MRI of brain, those segmentation have several rewards and drawbacks. These rewards and drawbacks have described very carefully with output are describe here. There are no such set of rules which always yield very good results for all type of MRI of brain images, thus a brief synopsis for different type of splitting up are discussed here. Though optimal selection of features, tissues, brain and non–brain origins are considered as main technical hitches for brain image segmentation.

There are several typical MR Image segmentation approaches as follows:

Thresholding Technique

Thresholding Technique is the classification of each pixel depends on its own information such as intensity and colour information. Those procedures are proficient when the histograms of objects and background are clearly separated. In thresholding based segmentation scheme, each image is divided into a number of segments by defining some threshold value. Thresholding is a very known and simple approach for segmentation in computer vision and image analysis [3].

As the computational complication is low, thresholding centered system is considered for real time computer vision systems. Thresholding scheme is broadly classified into two categories:

1. Contextual [4] (depends on second order gray level statistics or co-occurrence matrix of the image).
2. Non-contextual [5] (depends on gray level distribution of image).

If only one threshold is used for entire image then it is called global thresholding. On the other hand if the image is partitioned into a number of sub-regions and threshold value is determined for each sub regions, it is referred to as local or adaptive thresholding [6] Further thresholding scheme can be divided into bi-level thresholding (when the processed output image will have two region types as background and foreground) or multi-level thresholding (when the processed output image will contain more than two region type). A simple approach of determining the threshold value/s is by analysing peaks and valleys of the histogram of the image. These peaks and valleys can be used for selecting threshold/s by minimizing the probability of error using Bayesian risk formulation.

A novel brain tumor segmentation scheme is addressed by Rajasvaran Logeswaran, Chikkannan Eswaran in [7], where the segmentation of the image is obtained by thresholding technique. In this paper, a pattern for introductory detection of tumors in 2D MRCP images was proposed.

The various execution stages of the scheme were accessible. In tests accompanied, the scheme was found to achieve high success rates in correctly classifying tumor and standard MRCP images. The arrangement could be improved further and some recommendations are presented here. The existing scheme uses Gaussian filtering for the duration of segmentation. Anisotropic filtering using algorithms such as the Euclidean Shortening Flow (ESF) may be attempted to better preserve the image structure. The threshold values used in various fragments of the algorithm may also be modified from side to side for better statistical analysis of a larger number of test images. Dynamic thresholding algorithms may be used. In an ancient work, an iterative selection thresholding based tumor detection scheme is proposed by Yu-Bu Lee et al. in [8], where a gradient magnitude based on region growing is used to detect the tumor from F-18-FDG PET images. Here the iterative selection thresholding is used to detect the images with tumors and organs.

Again in presence of noise, thresholding based segmentation scheme will not produce a reasonable solution for brain tumor detection. So it is expected that thresholding scheme will not be able to segment a target with proper shape and orientation. A better result can be obtained with proper accuracy by region based segmentation schemes like region growing (includes the schemes like relaxation labelling, region splitting and merging, graph-cut etc.) and watershed segmentation scheme as it uses both spatial and gray level information of an image. In the following paragraphs we are going to discuss a few of these approaches in detail.

Region Growing Technique

The concept of Region-based segmentation is to extract features (similar texture, intensity levels, homogeneity or sharpness) from a pixel and its neighbours is utilised to derive relevant information for each pixel. Region growing approach of segmentation is a well-known spatial segmentation scheme in image analysis and computer vision. In this scheme segmentation starts with some initial seed point selection using some predefined criteria. These seed points act as the initial points of different regions available in the considered image. As the region growing process starts, the neighbouring pixels of a seed point from a particular region are tested for homogeneity and are added to a particular region. In this approach each pixel in that image is consigned to a particular region in the segmented image. After region growing is concluded region merging is executed, different regions of the image are merged to a single region with some similarity criteria. Region growing technique is simple and can correctly separate the image pixels that have similar properties to form large regions or objects. As this approach depends on the spatial correlation of pixels in an image, the segmented output is expected to be better as compared to the histogram thresholding based scheme.

Chang et al., (1994) projected a region-growing structure for image segmentation. This process is guided by regional character study and no factor tuning or a priori knowledge about the image is required. The image is first divided into many minor primitive regions that are supposed to be homogeneous. These primitive regions are then merged to arrange larger regions up until no more merges are probable. Two similar regions are further merged if they pass the homogeneity or uniformity test and further if the value of the edge linking them is weak [9].

For region growing method, seeds could be automatically or manually chosen. Their automated selection is based on separating pixels that are of concern, e.g. the brightest pixel in an image can work for as a seed pixel. They can also be separated from the mounts found in an image histogram. On the other hand, seeds can also be selected manually for every entity present in the image. The method is employed to segment an image into different regions using a set of seeds. Each seeded region is a linked component encompassing of one or more points and is represented by a set S. The set of close neighbours bordering the pixel is calculated. The neighbours are then examined and if they intersect any section from set S, after that a measure δ (difference between a pixel and the intersected region) is computed. If the neighbours transect more than one region, then the set is taken as that region for which difference measure δ is maximum. The new state of regions for the set then establishes input to the next iteration. This process continues until the complete image pixels have been integrated into regions [9].

Another approach of region based segmentation scheme includes graph-cuts, where the image segmentation problem is considered as a graph partitioning problem and each pixel of the image frame is represented by a point in the graph. The pixels in the image are partitioned in to a region by pruning the weight of the graph. The demonstration of this algorithm is well illustrated in the works. As the result obtained by the region growing scheme suffers from over - segmentation / under-segmentation, it is found that region growing scheme may not be able to give good object boundary for brain tumor detection. So some parts of object may be found to be identified as background or some parts of background may found to be identified as object. This effect is named as effect of silhouette by Liu and Sarkar in their article. In the succeeding section we have described different approaches for detecting objects with proper boundaries.

Watershed Technique

Watershed algorithm is another approach of performing region based spatial segmentation, using gray level morphological operation. The intuitive idea underlying watershed algorithm comes from the field of water topography: a drop of water falling on a surface follows a descending path and eventually reaches to a minimum. Watershed lines are the dividing lines of the domains of attraction of these drops of water. An alternative approach is that where it is imagined that the surface is being immersed in a lake, with holes pierced in local minima. Water will fill up basins starting at these local minima, and at points which are considered where waters coming from different basins would meet, dams are built. Therefore the surface is partitioned into regions or basins separated by dams, called watershed lines.

An early work using watershed segmentation scheme for object detection is proposed by Johan Debayle, Jean-Charles Pinoli [10], where watershed algorithm is used for object boundary identification and to avoid over-segmentation. Watershed segmentation performed to extract good markers of its objects, the cells. The watershed transformation is a very powerful morphological operation and whose use for segmentation was described and illustrated in numerous recent publications. Given a set of markers and an image f regarded as a topographic relief, "marker-driven" watershed segmentation allows the image expert to remove the highest crest-lines of *f* separating two markers. Usually, one chooses for f a gradient-image, since the object's contours is usually understood as the highest crest-lines of the gradient around the object's marker.

The watershed transformation is now well recognized as being a fundamental step in many powerful morphological segmentation processes [11]. It has been made computationally practical thanks to a fast technique presented by Vincent and Soille [12]. Watershed analysis subdivides the image, considered as a topographic surface, into low-gradient catchment basins surrounded by high-gradient watersheds. A catchment basin consists of a homogeneous set of points that are all connected, through a path, to the same minimum altitude point. The watersheds are made up of connected points exhibiting local maxima in gradient magnitude; in order to yield a final segmentation, these points are typically absorbed into adjacent catchment basins. The region based segmentation scheme which are discussed here, are: region growing, relaxation labelling and watershed segmentation scheme, which may suffers from over segmentation result. Again in illumination variation condition these approaches hardly give any good impressions. Hence detection of moving object with accurate object boundary in illumination variation is found to be an ill-posed problem. It is known that edge based approach is less sensitive to variation in illumination condition. Hence use of any edge detection scheme for finding the object boundary will be always a way out to get over this proper boundary detection problems.

Edge Extraction Technique

Edge-based approaches are concentrated on detecting contour. They fail when the image is blurry or too complex to identify a given border. The most important feature in an image is the contrast. Contrast may be described as discontinuities in the gray values of an image or variations in scene illumination. In vision based analysis edge is well-thought-out as a very effective descriptor of contrast.

Different approaches of edge detection in an image includes gradient based edge (includes Sobel, Perwitt and Robert operators), Canny edge, Fuzzy edge, Laplacian of Gaussian (LOG), Laplacian edge etc. Most of the edge extraction based object detection scheme depends on the luminance information of the image. In an ancient work, H. Tang et al. in [13] considered the purpose of the multi-resolution image analysis is to decompose the image into multi-frequency representations to think about subjects of interest in variable resolutions. Multi-scale filtering includes filters such as the canny and the Monga-Deriche filter which can detect the edges in the low contrast or low S/N images. These include among good edge detectors since they follow the optimal filter design criteria: good localization and high S/N output. By adjusting the scales from low to high, separating edge from fine to coarse can be obtained. Here they employ a multi-resolution segmentation concept to segment both edges and structures. Instead of using the local statistic standard deviation as the edge strength detector, they define a new Ti/ as the edge strength detector using the Monga-Deriche low-pass filter that can be realized using recursive digital filter design. Edge extraction based scheme delivers an effectual object detection result against illumination variation in the scene but it has its own drawbacks. The major limitation of the edge-based approach of object detection scheme is its inability to produce a reasonable solution in cluttered background. In case of two or more objects present (overlapped with each other) in the scene the effect of silhouette is also likely to occur as one of the objects may not able to be identified in the image. Many of the edge detection problems can be eliminated by the active contour detection schemes. Active contours are deforming dynamic curves defined within an image which are capable to move under the effect of internal and external forces derived from the image data. It can be specified through a function and a differential equation controlling the contour causes it to evolve so as to reduce its energy to minima that correspond to the desired region boundaries. Few examples of the active contour approaches include: snake model, balloon model, gradient vector field snake, and level set approaches. The details of these approaches can be obtained in the surveys like [14]. However these approaches have a limitation of getting stuck at local minima and also highly sensitive to starting point.

Statistical Approaches

In this style of technique labels pixels according to probability values, which are determined based on the intensity distribution of the image. Provided a suitable theory about the distribution, statistical techniques attempt to solve the problem of estimating the related class label, provided only the intensity for each pixel. Such an estimation problem is necessarily formulated from an established criterion.

MRF Model based Technique

Generally the variation in the gray level intensity, colors and appearance on a real world image arises due to the causes of non-uniform lighting, random fluctuations in the object surface orientation, textures or noise. These spatial gray level ambiguities of the image make the non-statistical spatial segmentation scheme very difficult for object detection. Hence, it requires some kind of stochastic methods to model the important attributes of an image so that a better segmentation result can be obtained than that of non-statistical approach based segmentation scheme. MRF a well-known statistical model be responsible for a convenient way to define contextual features of an image such as image gray values, edge, entropy, color, texture, motion etc. This is achieved through characterizing mutual influences among such entities using conditional probability distributions. The MRF theory tells a way to model the a priori probability of contextual dependent patterns, such as textures and object features. MAP probability is one of the most popular statistical criteria for optimality and in fact, has been the most popular choice in vision group.

ANN image segmentation techniques

Artificial Neural Network Image Segmentation Procedures initiated from clustering algorithms and pattern recognition methods. They commonly aim to develop unsupervised segmentation algorithms. Sometimes, the above segmentation approaches are overlain and can be collective. Several brain MRI segmentation techniques using neural networks are reviewed in literature [15]-[17]. The most famous unsupervised approach using ANN, the self-organizing feature maps (SOFM), developed by Kohonen [18] is a strong candidate for continuous valued unsupervised pattern recognition.

In an ancient work, Yan Li and Zheru Chi [19] developed a new unsupervised MRI segmentation method based on the SOFM network. The algorithm includes spatial constrictions by using a Markov Random Field (MRF) model. Many researchers have applied the MRF to model the spatial constrictions in supervised and semi-supervised segmentation set of rules [20]. In that paper, Yan Li and Zheru Chi [19] model the contextual data in the brain MRI with MRF and add the model in the SOFM learning. The MRF term familiarizes the prior distribution with clique potentials and thus progresses the segmentation results.

Cooperative Hierarchical Computation Approach

These techniques use pyramid structures to relate the image properties to an array of father nodes, opt for iteratively the point that average or associate to a definite image value. Beaulieu & Goldberg (1989) proposed a hierarchical step by step optimization set of procedures for region integration, which is based on stepwise optimization and produces a hierarchical decomposition of the image. The algorithm begins with an initial image separating into a number of regions. At each iteration, two segments are merged provided they minimize criteria of merging a segment to another. In this stepwise optimization, the algorithm pursuits the entire image context formerly merging two segments and finds the optimal pair of segments. This means that the most analogous segments are combined first. The algorithm gradually merges the segments and produces a sequence of partitions. The arrangements of partitions imitate the hierarchical structure of the image.

Density–based Approach

Utmost partitioning methods cluster objects centered on the distance among objects. Such methods can find only spherical – shaped cluster and encounter difficulty at discovering clusters of arbitrary shapes. Other clustering methods have been developed based on the notion of density.

Here they use the density based approach using dissimilarity matrix to select the seed points which are the most appropriate cluster center. The general idea is to continue growing the specified cluster as much as the density (number of objects or data points) in the “neighbourhood” exceeds some thresholds; which means, for every single data point inside a given cluster, the neighbourhood of a given radius must contain no less than a minimum stated numeral of points. This type of method can be used to filter out noise (outliers) and discover clusters of arbitrary shape.

Sometimes, tumors have similar intensity characteristics of non-brain tissues like fat, muscles and background clutters. Hereafter the brain portion must be extracted firstly to eradicate these overlapping intensity artefacts. These methods next checks for further presence of any abnormality is within the slice and distinct between the normal slices and abnormal slices. In case of normal slices, the vertical central line is symmetrical about the CSF. So the presence of abnormal tissues in the CSF class could be identified by quantifying the vertical symmetry of the CSF image. Therefore to produce a CSF image from extracted brain portion a fuzzy segmentation is done and a fuzzy symmetric measure (FSM) is intended for CSF image to differentiate amongst normal and abnormal scans. In CSF region tumor looks as if an increased MR image intensity which possesses local maxima. Hence to remove the section with maximum intensity from the CSF class and select them as region of tumors extended maxima transform is used.

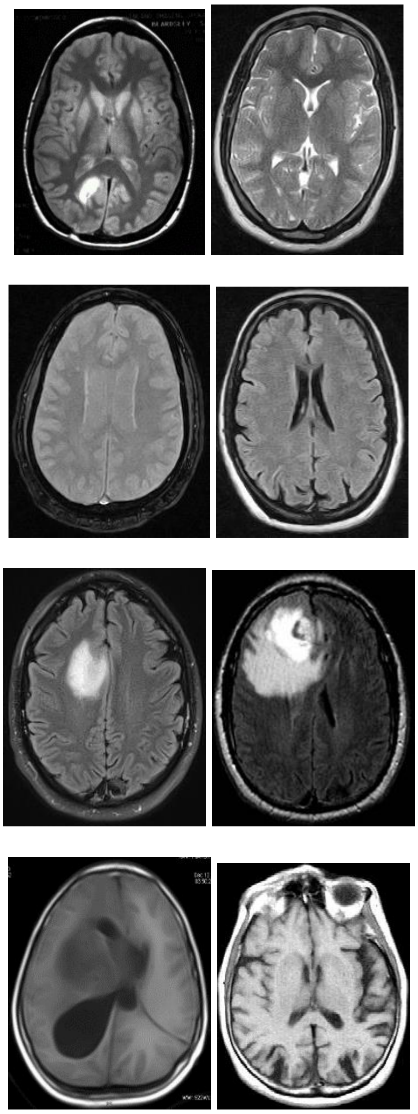


Figure 1: Example Medical resonance imaging data

III. CONCLUSION

The undesirable background removal are important for Quality enhancement and filtering such as edge sharpening, enhancement, noise removal to obtain improved image quality as well as the detection procedure. Among the different filtering techniques deliberated in above mentioned techniques, median filter suppressed the noise without blurring the edges and it is superior outlier even without dropping sharpness of the images, mean filter are much greater sensitive than that of median filter in the circumstance of smoothing out the image. Gaussian reduces the noise; enhance the image quality and computationally further efficient as compared to other filtering methodology. After the several image quality improvement and noise reduction discussion here, several of the possible segmentation methodology like binarized segmentation based on intensity, based on Region, based on classification, based on texture, based on clustered, based on neural network, based on fuzzy, based on edge, based on atlas, based on knowledge, based on fusion, based on probabilistic segmentation has been briefly described above with short details, advantage and disadvantage to detect or segment a brain tumor from MRI of brain image. Most of the binarized fails due to large intensity difference of foreground and background i.e. the black or dark background of MRI image. The region growing methodologies are mostly not included in standard methods for validate segmentation; the main problem includes low quality of segmentation in the border of tumor. These methods are good for homogeneous tumor but not suitable in case of heterogeneous tumor. Segmentation techniques that are based on classification segment tumor accurately and produce good results for large data set but display undesirable behaviours can in those case where a class is under represented in training data. Clustered based segmentation provides quite simple, quick and yield good results for non-noise image but for noise images it leads to severe erroneousness in the segmentation. In neural network based segmentation performance is little better on noise field and there is no need of assumption of any necessary data distribution but learning process is one of the great disadvantages of it. In case of edge based segmentation better performance is given by canny but other noise edges are also produce, sober gives very effective outcomes but shortcoming of it is the discontinuity of edges. In the case of a weak border or when any gap is present in the border of the tumor, the contour or surface area may outflow to extra regions. Even in presence of several detriments, the automization of brain tumor segmentation by means of grouping of procedures based on threshold technique and grouping like SVM, Basian may overcome the problems and offers actual and precise results for brain tumor detection.

REFERENCES

[1] Cobzas, D., Birkbeck, N., Schmidt, M., and Jagersand, M., "3d variational brain tumor segmentation using a high dimensional feature set", in [MMBIA in conjunction with ICCV], (2007).

[2] Sudipta Roy, Prof. Samir K. Bandyopadhyay, "Detection and Quantification of Brain Tumor from MRI of Brain and it's Symmetric Analysis", International Journal of Information and Communication Technology Research(IJICTR), pp. 477-483,Volume 2, Number 6, June 2012.

[3] M. Sezgin and B Sankur, "Survey over image thresholding techniques and quantitative performance evaluation", Journal of Electronic Imaging, 13(1):146–165, 2004.

[4] Wen-Nung Lie, "Automatic target segmentation by locally adaptive image thresholding", EEE Transaction on Image Processing, 4(7):1036–1041, 1995.

[5] K. V. Mardia and T. J. Hainsworth. "A spatial thresholding method for image segmentation", IEEE Transaction on Pattern Analysis and Machine Intelligence, 10(6):919–927, 1988.

[6] R. F. Gonzalez and R. E. Woods. "Digital Image Processing". Pearson Education, Singapore, 2001.

[7] Rajasvaran Logeswaran, Chikkannan Eswaran, "Discontinuous Region Growing Scheme for Preliminary Detection of Tumor in MRCP Images", in Springer Science Business Media, Inc. 2006.

[8] Yu-Bu Lee, Soo-Min Song , Jae-Sung Lee, Myoung-Hee Kim, "Tumor Segmentation from Small Animal PET Using Region Growing based on Gradient Magnitude", IEEE, 2005.

[9] R. B. Dubey, M. Hanmandlu, S. K. Gupta and S. K. Gupta , "Region growing for MRI brain tumor volume analysis", in Indian Journal of Science and Technology, Vol.2 No. 9, Sep 2009.

[10] Johan Debayle , Jean-Charles Pinoli, "Spatially Adaptive Morphological Image Filtering using Intrinsic Structuring Elements," in Image Anal Stereol, IEEE, 2005.

[11] S. Beucher and F. Meyer, "The morphological approach to segmentation: the watershed transformation," in Mathematical Morphology in Image Processing, E. Dougherty (Ed.), N.Y., U.S.A., pp. 433–481, 1993.

[12] L. Vincent and P. Soille, "Watersheds in Digital Spaces: An Efficient Algorithm based on Immersion Simulations," IEEE Transaction on Pattern Analysis and Machine Intelligence, Vol. 13, No. 6, pp. 583–589,1991.

[13] H.Tang, EX Wu, Q.Y.Ma, D.Gallaghe, "Multiresolution MRI Brain Image Representation and Segmentation," in Proc. Intl. Sot. Mag. Reson. Med. 8, 2000.

[14] G. Heo and C. G. "Small Form representations and means for landmarks: A survey and comparative study", Computer Vision and Image Understanding, 102(2):188–203, 2006.

[15] C. A. Parra, K.Iftekharuddin and R. Kozma, "Automated brain data segmentation and pattern recognition using ANN," in the Proceedings of the Computational Intelligence, Robotics and Autonomous Systems (CIRAS 03), December, 2003.

[16] I. Middleton and R. Damper, "Segmentation of Magnetic Resonance Images using a combination of Neural Networks and Active Contour Models," in Medical Engineering & Physics, No. 26, pp. 71-86, 2004.

[17] J. Vesanto and E. Alhoniemi, "Clustering of the Self-Organizing Map", IEEE Transactions on Neural Networks, Vol. 11, No. 3, pp. 586-600, May 2000.

[18] T. Kohonen, "Self-organization and Associative Memory". Springer-Verlarg, 1989.

[19] Yan Li and Zheru Chi, "MR Brain Image Segmentation Based on Self-Organizing Map Network," in International Journal of Information Technology Vol. 11, No. 8, 2005.

[20] Y. Zhang, M. Brady and S. Smith, "Segmentation of Brain MR Images through a Hidden Markov Random Field Model and the expectation-Maximization Algorithm," in IEEE Transactions on Medical Imaging, Vol. 20, No. 1, pp. 45-57, January, 2001.