
Introduction

1. INTRODUCTION

A brain tumor is a cluster of abnormal cells growing in the brain. A tumor that begins and tends to keep growing in the brain is called Primary brain tumor where as metastatic brain tumors are those which appear as cancer elsewhere in the body and start migrating to the brain. There are more than 120 different types of brain tumors; some are malignant (cancer), and some are benign (noncancerous). The cause of brain tumors is still unknown. Benign or malignant, primary or metastatic, brain tumors are treatable. More 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 Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Functional MRI (fMRI), Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT) in medical imaging. Imaging techniques are used to diagnose, stages of brain tumors. MRI is the commonly used technique for detecting the abnormality of medical images.

The existing tumor detection methods are broadly classified into three categories: atlas-based methods (Cuadra, M.B et al,2004), (Moon, N et al,2002) symmetry property-based methods (Khotanlou, H et al,2009),(Wang, Z et al,2004),(Mancas, M et al,2005) and feature-based methods (Lau, P.Y et al,2004) Most of the methods are semi-automatic and require user intervention either to initiate or to refine the results.

Radiation Oncologists and many other medical experts currently spend a substantial amount of their time segmenting medical images, and in particular, labeling brain tumors and associated edema in MRI. This labeling is especially important when planning for radiation therapy. Introducing techniques such as Intensity-Modulated Radiation Therapy increases the workload of segmentation (Woo, S.Y et al, 1999). The introduction and acceptance of these types of new technology will thus depend on reducing the manual time associated in detecting and segmenting tumors.

Over the past 15 years, an immense amount of research has focused on semi-automatic and fully automatic methods for detecting and/or segmentation brain tumors in MRI scans, but the tools used in practice still rely on significant manual interaction, which is based on the data, and there lies difficulty in translating complex anatomic knowledge into a series of operations which have good generalization properties.

1.1 Magnetic resonance imaging

MRI is also known as nuclear magnetic resonance imaging or magnetic Resonance Tomography. It is used for visualizing the detailed internal structures of the brain. MRI uses the nuclear magnetic resonance (NMR), property whose image nuclei of atoms are situated inside the body. MRI provide a contrast between soft tissues of the body which is useful in imaging the brain, muscles, the heart and cancers compared with other medical imaging techniques such as CT or X-rays. Unlike CT scan or traditional X-rays, MRI does not use the ionizing radiation.

The typical MRI imaging system mainly consists of five parts: the main magnet, gradient systems, Radio Frequency (RF) system, computer systems and other auxiliary equipment (<http://jinshungroup.com/ProductShow.asp?ID=92> [J/OL]), as shown in Figure 1.1.

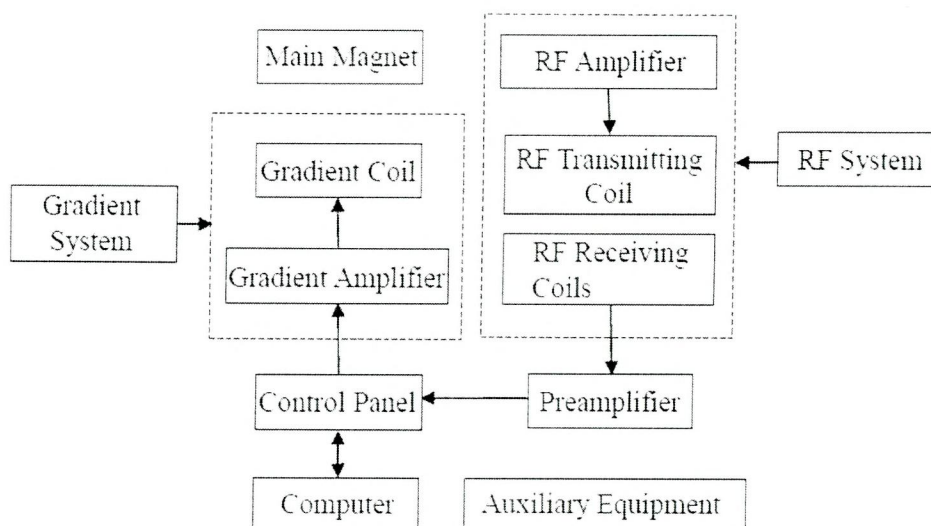


Figure 1.1: Structure of MRI imaging System

The MRI scanner which forms a strong magnetic field around the area to be imaged. Most medical applications rely on detecting a radio frequency signal emitted by excited hydrogen atoms in the body (present in any tissue containing water molecules) using energy from an oscillating magnetic field applied at the appropriate resonant frequency. The orientation of the image is controlled by varying the main magnetic field using gradient coils. As these coils are rapidly switched on and off they create the characteristic repetitive noises of an MRI scan. MRI scan image is shown in Figure 1.2.

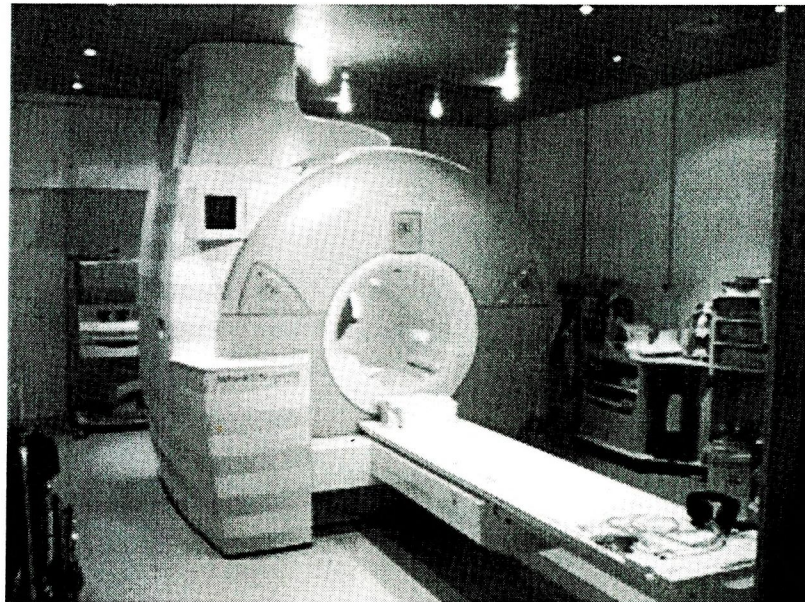


Figure 1.2: MRI scan image

1.2 Brain tumors

Tumor

A tumor is known as a neoplasm, is an abnormal mass of tissue which may be solid or fluid-filled. A tumor does not mean cancer. The tumors can be benign (not cancerous), pre-malignant (pre-cancerous), or malignant (cancerous). There are many different types of tumors with manifold names. These names usually reflect their shape and the kind of tissue they appear in. A tumor is a kind of lump or swelling, which does not necessarily pose a health threat.

Brain Tumor

A brain tumor is a localized intracranial lesion which occupies space with the skull and tends to cause a rise in intracranial pressure. The following Figure 1.3 shows the types of tumor.

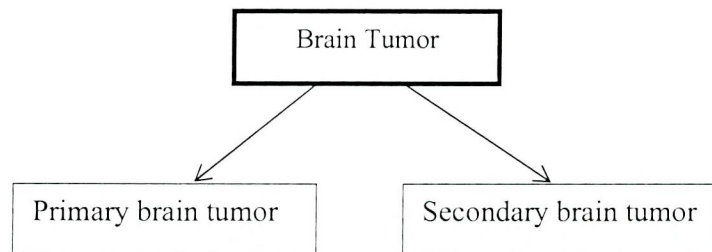


Figure 1.3: Types of tumor

Gliomas and meningiomas are the most common primary brain tumors. Gliomas are thought to be derived from glial cells such as, oligodendrocytes, astrocytes and ependymal cells. Gliomas are classified into four grades by the World Health Organization (WHO) on the basis of their histologic features and malignancies. Glioblastomas are considered grade IV; the most aggressive and malignant type of brain tumor. Secondary brain tumors are referred to as metastases. They do not initiate in the brain, but rather metastases occur when cancer cells break away from a primary tumor site elsewhere in the body and travel to the brain through the blood system.

1.2.1. Primary Brain Tumor: GlioblastomaMultiforme

GlioblastomaMultiforme (GBM) is the most lethal and aggressive form of primary brain tumor. It is a grade IV type of brain tumor. The survival rate of patients with glioblastoma is 12-15 months (Yang, I et al, 2009). GBM is derived from the malignant transformation of glial cells (Ray, S.K et al, 2010). Despite recent advances in radiation, chemotherapy, surgical techniques, and newer investigational drugs, GBM has a poor prognosis. Medical imaging plays an important role in the diagnosis of GBM. Typically post-contrast magnetic resonance (MR) imaging is used for diagnosis followed by biopsy for pathological validation. GBM often appear as ring-enhancing lesions on post-contrast MR images (Figure 1.4) .Treatment options for patients with GBM are determined by tumor size, location, and the associated symptoms. The current standard treatment for patient with GBM is surgical resection of the tumor followed by radiation therapy and concomitant and adjuvant temozolomide chemotherapy.

This approach is shown to standardize treatment and prolong survival for patients. Radiation therapy damages the genetic material (DNA) within tumor cells and limits their reproductivity. Tumor cells are less prone to repair DNA than healthy cells. With each subsequent radiation dose, the cumulative effects of unrepaired DNA strand breaks, and this initiates apoptosis (cell death) in these tumor cells (Baskar, R et al, 2012).

Radiation injury (RI) is an undesirable but unavoidable side effect of radiation treatment. Radiation injury is characterized by extensive necrosis due to small artery injury and direct damage to oligodendroglia. The incidence of radiation injury depends on the total radiation dose and the rate of delivery. Concomitant chemotherapy enhances radiation injury. RI appears as enhancing lesions on MR imaging. Since GBM is a high grade tumor, recurrences are common even after treatment, and these recurrences appear as hyper intense regions on post-contrast MR images.

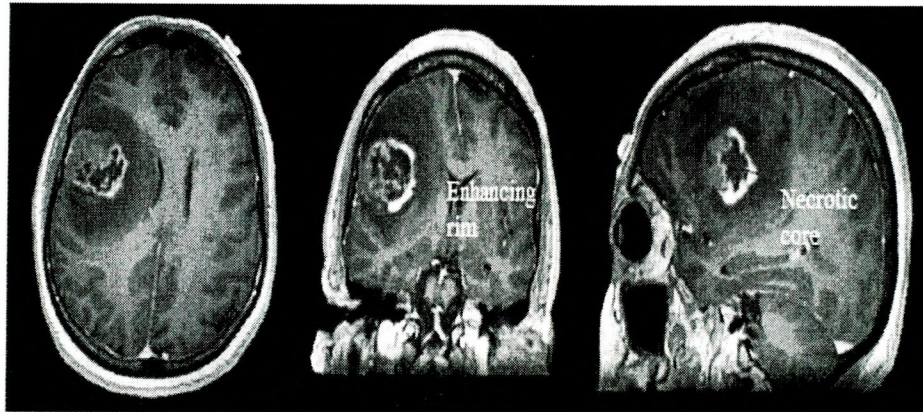


Figure 1.4: Post-contrast T1-weighted image of patient with glioblastoma

All of the above techniques seem to be promising, but none of them have been able to convincingly differentiate radiation injury from tumor recurrence. FDG-PET and dynamic contrast enhanced CT have shown better sensitivity and accuracy compared to other techniques. However, with the limited availability of Positron emission tomography (PET) scanners and the risks associated with radiation exposure from CT, the search for an accessible and reliable technique continues till date.

1.2.2. Secondary Brain Tumor: Metastasis

Brain metastasis is common among patients with systemic cancer. They are a significant public health issue, with 20–40% of patients with solid tumors subsequently developing symptomatic brain metastases (Barnholtz-Sloan, JS et al, 2004). Approximately 150,000 brain metastases are diagnosed annually in the United States. Brain metastasis (MET) is thought to occur when the primary tumor acquires the ability to migrate away from the primary site and travels to the brain. The most common origins of brain metastasis are from breast cancer, melanoma and lung cancer. Metastasis often causes severe neurological symptoms that significantly impair quality of life. With recent improvements in diagnostic imaging and increasing patient survival due to improved systemic cancer control, the incidence of intracranial metastatic disease is projected to rise. Imaging is the most important diagnostic modality for brain metastasis. Metastasis appears in enhancing necrotic core and on a post-contrast MRI. The management of brain metastasis initially involves treating the symptoms using corticosteroids, anticonvulsants to reduce peritumoral edema and prevent recurrent seizures and surgical resection for de-bulking followed by

therapeutic approaches of whole brain radiotherapy (WBRT), stereotactic radio surgery (SRS), and/or chemotherapy.

1.3 Image processing for MRI images

Image Processing is a technique to enhance raw images. Various techniques have been developed in Image Processing. The common steps in image processing are image scanning, storing, enhancing and interpretation.

The various image processing techniques are:

- Image preprocessing
- Clustering
- Feature Extraction
- Segmentation

1.3.1 Image preprocessing:

Preprocessing images commonly involves removing low-frequency background noise, normalizing the intensity of the individual particles images, removing reflections, and masking portions of images.

The preprocessing functions can be divided into two basic groups:

- Pixel operation
- Local operation

Pixel operation: It computes the brightness of a pixel in the output image exclusively from the brightness of the corresponding pixel in the source image. This group also encompasses image arithmetic functions which combine several images. These functions only use a single pixel on a fixed position from each of the source images. Pixel operations can be further divided into homogeneous and inhomogeneous pixel operations. Homogeneous operations use the same transformation function for each pixel, and inhomogeneous is the transformation function depends on the location of the pixel in the image.

Pixel operations are,

- Gray scale transformations
- Image arithmetic

Gray scale transformations: Gray-scale images represent data per element in a shade of gray that ranges in intensity from zero (being black) to a maximum (being white) with various shades in between. For example, an 8-bit gray scale will range from 0 to 255, providing 256 different possible levels of brightness.

Image arithmetic: An image is represented in a matrix format. To perform image arithmetic the size of the two matrices should be same. The operation on two images results in a new image. The arithmetic operations are addition, subtraction, multiplication, division.

Local operation: It takes a certain neighbourhood of the current pixel into account when computing the brightness of the corresponding output image pixel. An example is the mean value filter, which sets the brightness of the output image pixel to the average brightness of a small neighbourhood of the corresponding point in the source image.

Local operations are discussed in the following sections:

- Linear filter
- Median filter
- Mean filter
- Morphological filter
- non-linear filter

Filter:

- Filter is a technique for modifying or enhancing an image.

For example: Filtering an image emphasizes certain features or removes other features.

Linear filter:

- Linear filtering is a fundamental image-processing method in which a filter is applied to an input image to produce an output image.
- It replaces each pixel by a linear combination of its neighbors. Average filter, Laplacian filter, unsharp masking filters are examples of linear filter.

Nonlinear filter:

- Nonlinear filters have different behavior compared to linear filters. It is more varied and difficult to categorize, and are still an active area of research. They are potentially more powerful than linear filters because they are able to reduce noise levels without simultaneously blurring edges.

Smoothing filter:

- Smoothing filter is a fast filtering algorithm that yield noise suppression power in order to preserve the high spatial frequency detail in an image.

Median filter:

- Median filtering is a nonlinear process which is used to remove noise. It is also useful in preserving edges in an image while reducing random noise.
- The median value is calculated by sorting all the pixel values from the window into numerical order, and then replacing the pixel value with the middle (median) pixel value.

Mean filter:

- Mean filtering is simply used to replace each pixel value in an image with the mean (average) value of its neighbors, including itself.

Spatial filter:

- Spatial filtering is the process of dividing the image into its constituent spatial frequencies, and selectively altering certain spatial frequencies to emphasize some image features.
- Three types of spatial filters are low pass filters, band pass filters, high pass filters.

Morphological filter:

- Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image, such as boundaries, skeletons, etc.

- Basic morphological operations are erosion, dilation, opening, closing.

1.3.2 Clustering

Clustering is the classification of objects into different groups, or more precisely, the partitioning of a data set into subsets (clusters), so that the data in each subset (ideally) share some common and it depicted with respect to defined distance measure. Clustering algorithms essentially perform the same function as classifier methods without the use of training data. Thus, they are termed unsupervised methods. To compensate for the lack of training data, clustering methods iteratively alternate between segmenting the image and characterizing the properties of each class.

Hierarchical clustering: Hierarchical clustering method works by grouping data objects into a tree of clusters. Hierarchical clustering doesn't require specifying the number of clusters. Hierarchical clustering is deterministic. There are 2 types of hierarchical clustering.

It contain 2 algorithms namely,

- **Agglomerative** ("bottom-up"): Agglomerative algorithms begin with each element as a separate cluster and merge them into successively larger clusters.
- **Divisive** ("top-down"): Divisive algorithms begin with the whole set and proceed to divide it into successively smaller clusters.

Partitional clustering: A partitional algorithm divides a data set into a single partition

- K-means clustering
- Fuzzy c-means clustering

K-means clustering:

- K-means clustering is an algorithm used to classify or to group the objects based on attributes/features into K number of group.
- K is positive integer number.
- The grouping is done by minimizing the sum of squares of distances between data and the corresponding cluster centroid.

Fuzzy c-means clustering:

- It is a method of clustering which allows one piece of data belonging to two or more clusters. It is based on minimization of the objective function.

1.3.3 Feature extraction:

Feature extraction is a special form of reduction. It involves simplifying the amount of resources required to describe a large set of data accurately. Feature extraction is a general term used for constructing combinations of the variables. It will describe the data with sufficient accuracy. The methodology analyses object and images to extract the most prominent features that are representative of the various classes of objects. Features are used as inputs to classifiers that assign them to the class that they represent.

The purpose of feature extraction is to reduce the original data by measuring certain properties, or features, that distinguish one input pattern from another pattern. The extracted feature should provide the characteristics of the input type to the classifier by considering the description of the relevant properties of the image into feature vectors.

Some of the features that should be extracted are discussed subsequently:

- **Shape Features** - Circularity, irregularity, Area, Perimeter, Shape Index
- **Intensity Features** – Mean, Variance, Standard Variance, Median Intensity, Skewness, and Kurtosis
- **Texture Features** – Contrast, Correlation, Entropy, Energy, Homogeneity, cluster shade, sum of square variance.

1.3.4 MRI segmentation approaches

There are several typical MRI segmentation approaches as follows:

- **Threshold techniques:** The classification of each pixel depends on its own information such as intensity and color information. Those techniques are efficient when the histograms of objects and background are clearly separated.

- **Edge-based segmentation:** Edge-based methods are focused on detecting contour. These methods fail when the image is blur or too complex to identify a given border.
- **Region-based segmentation:** These method employs the concept of extracting features (similar texture, intensity levels, homogeneity or sharpness) from a pixel and its neighbors is exploited to derive relevant information for each pixel.
- **Cooperative hierarchical computation approach:** These method use pyramid structures to associate the image properties to an array of further nodes and then selecting iteratively the point that average or associate with the image.
- **Statistical approaches:** These methods label pixels according to probability values, which are determined based on the intensity distribution of the image. With a suitable assumption about the distribution, statistical techniques attempt to solve the problem of estimating the associated class label, when only the intensity for each pixel is given. Such an estimation problem is necessarily formulated from an established criterion.
- **ANN image segmentation techniques:** These techniques originated from clustering algorithms and pattern recognition methods. They usually aim to develop unsupervised segmentation algorithms.
- **Density-based Approach:** Most partitioning methods cluster objects based on the distance between 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.
- **Hierarchical Self-Organization Map segmentation:** The SOM is an unsupervised learning algorithm which is commonly used to visualize high-dimensional data on a two-dimensional screen .The Hierarchical Self-Organizing Map (HSOM) is an extension of the conventional (single-layer) Self-Organizing Map (SOM).

1.4. Tumor detection in multiple MRI sequences

In (W.B. Dou et al, 2007), according to the fuzzy set theory, tumor information in different sequences are modeled using the membership functions on each MRI sequence, and then all the obtained fuzzy sets are segmented together. The difficulty of this algorithm lies in the selection of membership function. A parametric smoothing model is proposed in (J.L. Marroquin et al, 2002), and the intensities of each category in T1-weighted images, T2-weighted images and PD-weighted images are handled by the Expectation Maximization (EM) algorithm. The final tumor segmentation results are synthesized by the fusion of models of each category. A hierarchical genetic clustering algorithm is exploited in (J.Y. Yeh et al,2008), which integrates the fuzzy learning vector quantization algorithm, called Hierarchical Genetic Algorithm with a fuzzy Learning Vector Quantization network (HGALVQ), to deal with T1-weighted images, T2-weighted images and PD-weighted images. The optimization criterion of hierarchical genetic algorithm is based on the minimization of the weighted error value and the complexity of local competitive network. The former of which was defined as the mean distance between the feature vector and its corresponding original image, and the latter of which is number of active nodes in the network. It is observed that the converged number of categories in algorithm is very large. In (K.M. Iftexharuddin et al,2009),the PSPTA algorithm (Piecewise Triangular Prism Surface Area) is used to extract fractal features and the Self-Organizing Map (SOM) (F.R. Bach et al,2004), is used to achieve the feature fusion. However, the accuracy of the system changes in a wide range so it is not very robust. In (K. Popuri et al,2009), their paper discussed about an algorithm which composed of a probabilistic model and active contour models for segmentation is applied to deal with T1-weighted images, T2-weighted images and T1-enhanced images. The algorithm relies on the extraction of the multi-dimensional features and the brief description of the natural information in the feature, but some of the assumptions used could not be apply to all patients. In (D. Cobzas et al,2008), two kinds of features, gray values of tissues and prior probability based on the alignment, are extracted by registration with the templates, and then data from manual separation are used as prior knowledge to train and learn a statistical classification model. The algorithm is very sensitive to the initial value of manual segmentation.

1.5 Motivation and objectives

According to the survey conducted by neuro-oncology disease management group (DMG) crude incidence of primary brain tumor in India is 3.4 per 100,000 populations for males and 1.2 per 100,000 populations for females. It represents less than 1% of tumor cases detected every year in the country. However, there has been an increase in the incidence of primary brain tumors over the last decade therefore segmenting brain tumors more accurately was felt as the need of the hour. Hence this research work was taken up to automatically segment the brain tumors.

In the proposed method, the execution time has been calculated while extracting the tumor region from MRI images, It takes less time while comparing with (S.Murugavalli et al. (2007), (T.Logeswari et al. 2010) .The objective of the thesis is:

1. To reduce the execution time.
2. To increase the segmentation accuracy.

1.6 Chapter formulation

The underlying objective of this research work is to adopt a segmentation method that uses Algometric clustering is to perform the pixel categorization in images. The methods and techniques used by these algorithms and the results obtained during experimentation are reported in this dissertation. The dissertation is organized as follows.

Chapter 1, Introduction provided a brief introduction to Magnetic Resonance Imaging, Brain Tumor, Basic Image Processing Methods, Fuzzy Theory-Based Method, MRI Segmentation Approaches and Tumor Detection in Multiple MRI Sequences. The motivation and objectives of the research work were also outlined in this chapter.

The literature review is a critical look at the existing research that is significant to the work that is carried out. A critical look at the various available literatures related to the present research work is given in **Chapter 2, Review of Literature**.

The method of extracting the Fuzzy along with the HSOM working of the Algeometric clustering is described in the **Chapter 3, Methodology**. The working of SVM classifier for finding the accuracy is also described in this chapter.

The SVM classifiers were tested vigorously with several brain tumor images and using performance metrics like accuracy and speed. The results obtained are presented and discussed in **Chapter 4, Results and Discussion**.

The conclusion of the research work is summarized along with future research directions in **Chapter 5, Summary and Conclusion**. The work of several researchers are quoted and used as evidence to support the concepts explained in this dissertation. All such evidences used are listed in the reference section of the dissertation.

Recognizing a brain tumor correctly at the right time and the right place is very important to ensure the detection in the MRI image at the time. This being the main underlying objective, the study proposes the use of brain tumor image processing and SVM classifiers for the segmentation. The field of fuzzy and HSOM is an active research area. The next chapter, Review of Literatures, briefs research work developed previously that are related to the present research work.