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Brain Tumor Detection through MR Images: A Review of Literature

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Abstract: *A brain tumor is an abnormal growth of tissue in the brain or central spine that can disrupt proper brain function and creates an increasing pressure in the brain. This paper is intended to present a comprehensive review of the methods of brain tumor detection through Magnetic Resonance Imaging (MRI) technique used in different stages of Computer Aided Detection System (CAD). It also provides a brief background on brain tumor in general and non-invasive imaging of brain tumor in order to give a comprehensive insight into the field. Lastly, the paper concludes with a concise discussion and provides a direction toward the upcoming trend of more advanced research studies on brain image segmentation and tumor detection.*

Keywords: *Brain Tumor, Central Nervous System (CNS), Cerebrospinal Fluid (CSF), Magnetic Resonance Imaging (MRI), Segmentation.*

I. Introduction

A brain tumor is a collection (or mass) of abnormal cells in the brain. A tumor may lead to cancer, which is a major leading cause of death and responsible for around 13% of all deaths world-wide. Cancer incidence rate is growing at an alarming rate in the world. So detection of the tumor is very important in earlier stages. Great knowledge and experience on radiology are required for accurate tumor detection in medical imaging. MRI is the most flexible of our diagnostic imaging modalities, possessing the ability to characterize a wide range of parameters in the living subject and provide exquisite spatial resolution. Brain tumor identification form magnetic resonance imaging (MRI) consists of several stages. Segmentation is known to be an essential but difficult step in medical imaging classification and analysis. Hence, it is highly necessary that segmentation of the MRI images must be done accurately before asking the computer to do the exact diagnosis. This review presents an overview of magnetic resonance imaging (MRI)-based medical image analysis for brain tumor studies.

1.1 Brain

Together, the brain and spinal cord (the central nervous system (CNS)) control the physiological and psychological functions of our body. Generally our brain includes three major parts:

1. Cerebrum. It controls thinking, learning, problem solving, emotions, speech, reading, writing, and voluntary movement.
2. Cerebellum. It controls movement, balance, and posture.
3. Brain stem. It connects the brain to the spinal cord, and controls vital functions in human body such as motor, sensory pathways, cardiac, repository and reflexes [1].

The brain is composed of two tissue types, namely gray matter (GM) and white matter (WM). Gray matter is made of neuronal and glial cells, also known as neuroglia or glia that controls brain activity and the basal nuclei which are the gray matter nuclei located deep within the white matter. The basal nuclei include: caudate nucleus, putamen, pallidum and claustrum. White matter fibers consist of many elinated axons which connect the cerebral cortex with other brain regions. The left and the right hemispheres of the brain are connected by corpus callosum which is a thick band of white matter fibers. Both, cerebellum and cerebrum have a very thin outer cortex of gray matter, internal white matter and small but deeply situated masses of the gray matter. The spinal cord is located toward the bottom of the brain. It has three structures: the midbrain, pons and medulla oblongata [2].

The brain also contains cerebrospinal fluid (CSF) which consists of glucose, salts, enzymes, and white blood cells. This fluid circulates through channels (ventricles) around the brain and the spinal cord to protect them from injury. There is also another tissue called meninges which are the membrane covering the brain and spinal cord [2].

Fig. 1 [3] shows the anatomy of the brain. It is composed of the cerebrum and the brain stem. The cerebrum occupies the

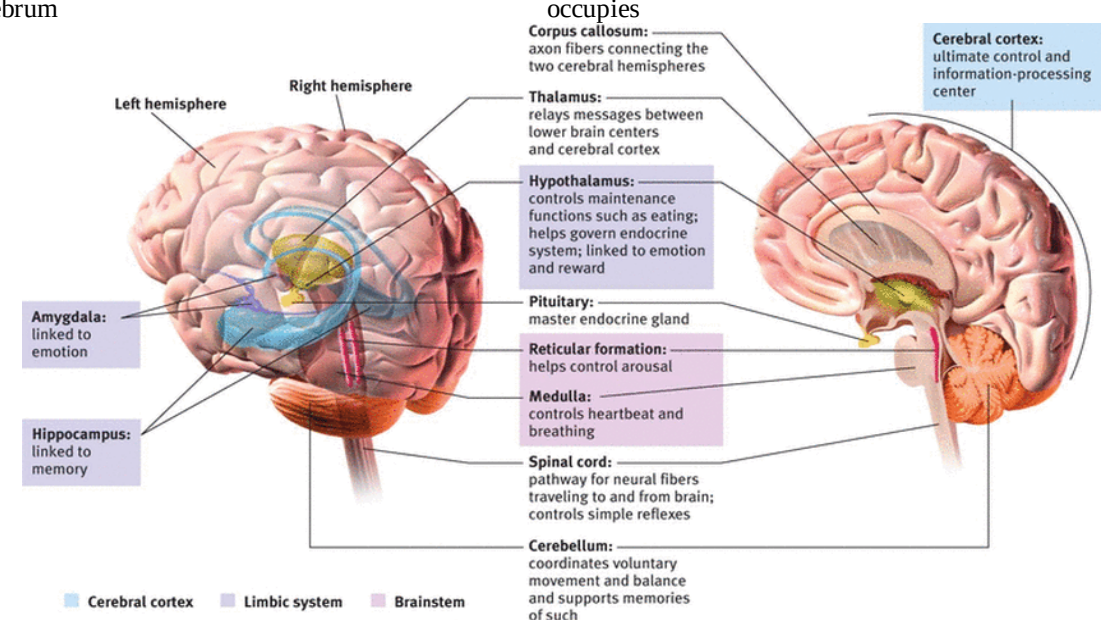


Fig. 1 Structure of Brain and its Functions.

Largest part of the brain. It is connected with the conscious thoughts, movement and sensations. It further consists of two halves, the right and the left hemispheres. Each controls the opposite side of the body. Moreover, each hemisphere is divided into four lobes: the frontal, temporal, parietal and occipital lobes as shown in Fig. 2 [3].

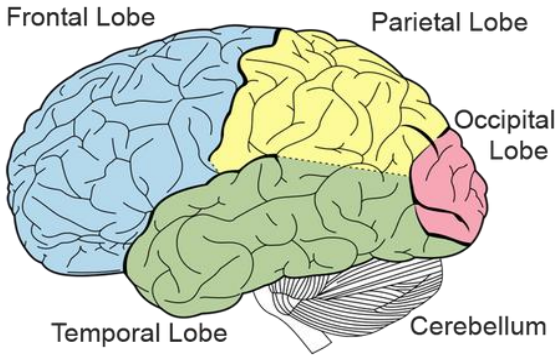


Fig. 2 Lobes of Human Brain.

Functions of lobes are:

1. Frontal Lobe**.** It is a portion of the cerebral cortex lying just behind the forehead. It is involved in speaking and muscle movements and in making plans and judgments.
2. Occipital Lobe**.** It is a portion of the cerebral cortex lying at the back of the head. It includes areas that receive information from the visual fields.
3. Parietal Lobe**.** It is a portion of the cerebral cortex lying at the top of the head and toward the rear. It receives sensory input for touch and body position.
4. Temporal Lobe**.** It is a portion of the cerebral cortex lying roughly above the ears. It includes the auditory areas, each receiving information primarily from the opposite ear [3]**.**

1.2 Brain Tumor

A brain tumor is an abnormal growth of tissue in the brain or central spine that can disrupt proper brain function and creates an increasing pressure in the brain. Due to increased pressure on the brain, some brain tissues are shifted, pushed against the skull or are responsible for the damage of the nerves of the other healthy brain tissues [4]. Brain and spinal cord tumors are different for everyone. They form in different areas, develop

from different cell types, and may have different treatment options. Scientists have classified brain tumor according to:

1. The type and grade (how aggressive it is),
2. Whether it is a primary or a secondary tumor,
3. If it is cancerous (malignant) or not (benign), and
4. Where in the brain the tumor is located [5].

The least aggressive type of brain tumor is often called a benign brain tumor. They originate from cells within or surrounding the brain, do not contain cancer cells, grow slowly, and typically have clear borders that do not spread into other tissue. They may become quite large before causing any symptoms. If these tumors can be removed entirely, they tend not to return. Still, they can cause significant neurological symptoms depending on their size, and location near other structures in the brain. Some benign tumors can progress to become malignant.

Malignant brain tumors contain cancer cells and often do not have clear borders. They are considered to be life-threatening because they grow rapidly and invade surrounding brain tissue. Although malignant brain tumors very rarely spread to other areas of the body, they can spread throughout the brain or to the spine. These tumors can be treated with surgery, chemotherapy and radiation, but they may recur after treatment.

Whether cancerous or benign, tumors that start in cells of the brain are called primary brain tumors. Primary brain tumors may spread to other parts of the brain or to the spine, but rarely to other organs. Metastatic or secondary brain tumors begin in another part of the body and then spread to the brain. These tumors are more common than primary brain tumors and are named by the location in which they begin. They are treated based on where they originate, such as the lung, breast, colon or skin. Each of these tumors has unique clinical, radiographic and biological characteristics [4].

1.3 Brain Tumor Grading

Tumors are given a name based on the cells where they arise, and a number ranging from 1–4, usually represented by Roman numerals I-IV. This number is called the "grade" and it represents how fast the cells can grow and are likely to spread. This is critical information for planning treatment and predicting outcomes.

Lower grade tumors (grades I & II) are not very aggressive and are usually associated with long-term survival. These appear almost normal under a microscope and can potentially be cured with surgery. Grade II tumor can invade adjacent normal tissue and can recur as a higher grade tumor. Higher grade tumors (grade III & IV) grow more quickly, can cause more damage, and are often more difficult to treat. These are considered malignant or cancerous. These appear abnormal under a microscope. Areas of dead cells (necrosis) in center tumors can contain several grades of cells; however, the most malignant cell determines the grade for the entire tumor (even if most of the tumor is a lower grade). Some tumors can change the way they grow and may become malignant over time [1].

1.4 Brain Tumor Types

The World Health Organization (WHO) has created a standard by which all tumors are classified. There are over 120 brain tumor classifications defined by the WHO, based on the tumor cell type and location, making this a very complex diagnosis. The most common primary tumor types found in adults are Gliomas, Meningiomas, Schwannomas, pituitary tumors, and CNS Lymphoma[1]. Gliomas begin from glial cells found in the supportive tissue of the brain. There are two types of gliomas Astrocytomas and Oligodendrogliomas, categorized by where they are found, and where the tumor begins. These begin in the supporting tissue cells (astrocytes) of the brain. In adults, they are most commonly found in the cerebrum where they cause pressure, seizures and personality changes. Astrocytomas are generally subdivided into low (grade I & II) or high grade (grade III & IV). High grade (grade IV) are the most malignant of all brain tumors, known as glioblastoma. Oligodendrogliomas tend to respond better to therapies and have a better prognosis than most other gliomas. They are grade II or III.

Meningiomas are usually slow-growing, benign tumors that come from the outer coverings of the brain just under the skull. This type of tumor accounts for about one third of brain tumors in adults. They may exist for many years before being detected and are commonly found in the cerebral hemispheres just under the skull [1].

Schwannomas are usually benign tumors that arise from the supporting nerve cells called vestibular schwannomas or acoustic neuromas. Vestibular schwannomas often cause hearing loss, or problems with balance or weakness on one side of the face. Surgery can be difficult because of where they are located. Sometimes radiation (or a combination of surgery and radiation) is used to treat these tumors [1].

The pituitary gland is located at the base of the brain and it produces hormones that control other glands in the body; specifically the thyroid, adrenal glands, ovaries and testes, glands for milk production in pregnant women, and the kidneys. Tumors in or around the pituitary gland can lead to problems with how these glands function. Also, patients may have vision problems. Pituitary tumors are frequently benign, and surgical removal is often the cure. Some are treated with medication to shrink or stop the tumor from growing [1].

CNS (Central Nervous System) Lymphoma is a malignant primary brain tumor that originates from the lymphocytes found in the brain, spinal cord, or eyes. It typically remains confined to the CNS. Treatment commonly includes chemotherapy and/or radiation [1].

II. Scan and Imaging Techniques

A scan is the first step to identify whether a brain tumor is present or not, and if present, locate exactly where it is growing. A scan creates computerized images of the brain and spinal cord by examining it from different angles. Some scans use a contrast agent (or a dye) to allow the doctor to see the difference between normal and abnormal tissue. A patient may need more than one type of scan to diagnose a tumor, depending on its type and location.

Commonly used scanning and imaging techniques [1]:

- Computed Axial Tomography (CAT or CT Scan) is a computerized x-ray that can show a combination of soft tissue, bone, and blood vessels. This is often the first test a person will receive in an emergency room (i.e. after a seizure).
- Magnetic Resonance Imaging (MRI) can create clear and detailed three dimensional images of a brain tumor. An MRI is not often used with people who have a pace maker or other metal device.
- Magnetic Resonance Spectroscopy (MRI Spect or MRS), measures the levels of metabolites in the body. An MRS can detect irregular patterns of activity to help diagnose the type of tumor, evaluate its response to therapies, or determine aggressiveness of a tumor.
- Perfusion MRI examines the flow of blood into the tissues to help assess the grade/aggressiveness of tumors and differentiate a recurrent tumor from dead tumor tissue.
- Functional MRI (fMRI) tracks the use of oxygen and blood flow in the brain as patients perform tasks. An fMRI can identify the motor, sensory, visual and language centres of the brain which helps your doctor carefully plan for surgery.
- Positron Emission Tomography (PET) scan uses a radioactive substance to visualize hypermetabolic activity such as with malignant cells, or abnormalities from a tumor or scar tissue. PET is also used during brain mapping procedures.
- Spinal tap (also called a lumbar puncture), uses a special needle placed into the lower back to measure pressure in the spinal canal and brain and determine if there is an infection or tumor cells.

2.1 Magnetic Resonance Imaging and Brain Tumors

Raymond V. Damadian invented MRI in 1969 and was the first person to use MRI to investigate the human body [6]. As shown in Fig. 3 [8]**,** Magnetic Resonance Imaging (MRI) is a powerful visualization technique that allows images of internal anatomy to be acquired in a safe and non-invasive way. It is based on the principles of Nuclear Magnetic Resonance (NMR). During MR imaging, the patient is placed in a strong magnetic field which causes the protons in the water molecule of the body to align in either a parallel (low energy) or anti-parallel (high energy) orientation with the magnetic field. Then a radiofrequency pulse is introduced which forces the spinning protons to move out of equilibrium state. When a radio frequency pulse is stopped, the protons return to equilibrium state and produce a sinusoidal signal at a frequency dependent on the local magnetic field. Finally, a radio frequency coils or resonators within the scanner detects the signal and creates the image [7]. This imaging medium has been of particular relevance for producing images of the brain, due to the ability of MRI to record signals that can distinguish between different 'soft' tissues (such as gray matter and white matter).

Brain images in MRI scan can be normal or abnormal. The normal brain is characterized by having gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF) tissues. The abnormal brain usually contains active tumor, necrosis and edema in addition to normal brain tissues. Necrosis is a dead cell located inside an active tumor, while edema is located near active tumor borders. Edemas, which results from local disruption of blood brain barrier, often overlap with normal tissues and it is always difficult to distinguish from the other tissues [9].

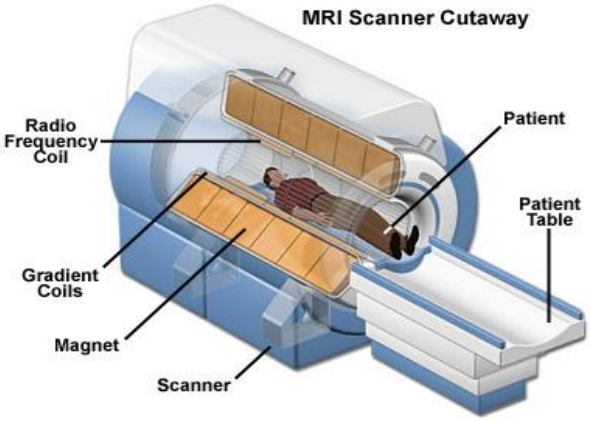
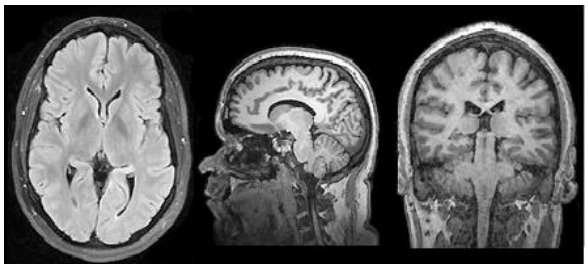


Fig. 3 MRI Scanner.

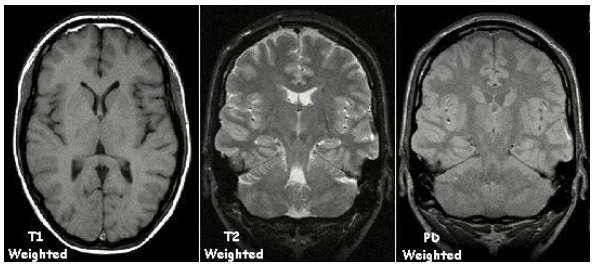
An axial MRI looks at the brain from below in a series of images starting at the chin and moving to the top of the head. A sagittal MRI looks at the brain from the side in a series of images starting at one ear and moving to the other. A coronal MRI looks at the brain from behind in a series of images starting at the back of the head and moving to the face as shown in Fig. 4 [10].



a) b) c)

Fig. 4 Brain MR Images from a) Axial Plane, b) Sagittal Plane, and c) Coronal Plane.

The signal processing has three different images that can be achieved from the same body: T1-weighted, T2- weighted and PD-weighted (proton density) as shown in Fig. 5 [11]**.**



a) b) c)

Fig. 5 Brain MR Images from Axial Plane a) T1-w, b) T2-w, and c) PD-w image.

The signal intensity on the MR image is determined by four basic parameters: 1) Proton density, 2) T1 relaxation time, 3) T2 relaxation time, and 4) Flow. Proton density is the concentration of protons in the tissue in the form of water and macromolecules (proteins, fat, etc). The T1 and T2 relaxation times define the way that the protons revert back to their resting states after the initial RF pulse. The most common effect of flow is loss of signal from rapidly flowing arterial blood [12].

The contrast on the MR image can be manipulated by changing the pulse sequence parameters. A pulse sequence sets the specific number, strength, and timing of the RF and gradient pulses. The two most important parameters are the repetition time (TR) and the echo time (TE). The TR is the time between consecutive 90 degree RF pulse. The TE is the time between the initial 90 degree RF pulse and the echo. The most common pulse sequences are the T1-weighted and T2-weighted spin-echo sequences.

The T1-weighted sequence uses a short TR and short TE (TR < 1000msec, TE < 30msec). The T2-weighted sequence uses a long TR and long TE (TR > 2000msec, TE > 80msec). The T2-weighted sequence is usually employed as a dual echo sequence. The first or shorter echo (TE < 30msec) is proton density (PD)

weighted or a mixture of T1 and T2. This image is very helpful for evaluating periventricular pathology, such as multiple sclerosis, because the hyperintense plaques are contrasted against the lower signal CSF. More recently, the FLAIR (Fluid Attenuated Inversion Recovery) sequence has replaced the PD image. FLAIR images are T2-weighted with the CSF signal suppressed [12].

When reviewing an MR image, the easiest way to determine which pulse sequence was used, or the "weighting" of the image, is to look at the cerebrospinal fluid (CSF). If the CSF is bright (high signal), then it must be a T2-weighted imaged. If the CSF is dark, it is a T1-weighted image. Thereafter, look at the signal intensity of the brain structures. On MR images of the brain, the primary determinants of signal intensity and contrast are the T1 and T2 relaxation times. The contrast is distinctly different on T1 and T2-weighted images. Also, brain pathology has some common signal characteristics [12].

2.2 Difficulties in segmentation of brain MRI

Cortical segmentation has not been made fully automated and operated at high speed because of the reliability of the MRI with regards to the homogeneity of its magnetic field. The problems of MRI include:

1. Noise: There is random noise connected with MR imaging system. This is known to have a Rician distribution [13].
2. Intensity non-homogeneity also called bias field or shading artifact: The non-uniformity in the radio frequency (RF) field during data collection results in shading effect [14].
3. Partial volume effect: In this type of effect more than one type of class or tissue occupies one pixel or voxel of an image. The pixels or voxels are called mixels [15].

III. Literature Review

Image segmentation [16] is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

In case of medical image segmentation the aim is to [16]:

- Study anatomical structure,
- Identify Region of Interest i.e. locate tumor, lesion and other abnormalities,
- Measure tissue volume to measure growth of tumor (also decrease in size of tumor with treatment), and
- Help in treatment planning prior to radiation therapy; in radiation dose calculation.

Using segmentation in medical images is a very important task for detecting the abnormalities, study and tracking progress of diseases and surgery planning. Segmentation must not allow regions of the image to overlap.

Objective of this review section is to present literature survey of image segmentation methods. The main goal is to highlight advantages and limitations of these methods. Key image processing techniques for brain MRI image segmentation are classified as thresholding, region-growing, clustering, edge detection, atlas-based, other methods etc. All these techniques are explained further in the following sections and many notable methods have been reviewed.

3.1 Thresholding based methods

Thresholding is one of the most generally used and oldest methods for image segmentation. In thresholding approach, image segmentation is based on gray level intensity value of pixels. Histogram of image is consists of peaks and valleys, where each peak represents one region. The valley between the peaks represents a threshold value. Histogram thresholding method is based on a concept that divides the image into two equal halves and histograms are compared to detect the tumor and cropping method is used to find a proper physical dimension of brain tumor. The threshold technique makes decision based on the local raw pixel information. It helps in extracting the basic shape of an image, overlooking the little unnecessary details. However, thresholding is often used as an initial step in a sequence of image segmentation process. Its main limitation is that only two classes are generated and it does not work when confronted with structures that lack clear borders [17].

Image segmentation through thresholding is considered to be a simple and powerful approach to segment the images that have light objects on dark background [18]. On the basis of thresholding value, there are two types of threshold values such as global and local thresholding [19]. The approach is called global thresholding when the T is fixed or constant. Otherwise, it is called local thresholding. If the background

illumination is uneven, the global thresholding is likely to fail. In local thresholding, multiple thresholds are used to compensate the uneven illumination [20].

3.2 Region growing based methods

In this technique, the images are partitioned by organizing the nearest pixel of similar kind (texture, intensity levels, homogeneity or sharpness). It starts with some initial seed point (pixel) selection using some predefined criteria. Accordingly the neighbouring pixels based on homogeneity criteria are appended progressively to the seed. This 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. After region growing is over region merging is performed, different regions of the image are merged to a single region with some similarity criteria.

In splitting process, region get divided into sub regions that do not satisfy a given homogeneity criteria. Splitting and merging can be used together and its performance mostly depends on the selected homogeneity criterion. Without tuning homogeneity parameters, the seeded region growing technique is controlled by a number of initial seeds. If the number of regions was approximately known & used it to estimate the corresponding parameters of edge detection.

For region growing, seeds can be automatically or manually selected. Their automated selection can be based on finding pixels that are of interest, e.g. the brightest pixel in an image can serve as a seed pixel. They can also be determined from the peaks found in an image histogram. On the other hand, seeds can also be selected manually for every object 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 connected component comprising of one or more points and is represented by a set S. The set of immediate neighbors bordering the pixel is calculated. The neighbors are then examined and if they intersect any region from set S, then a measure δ (difference between a pixel and the intersected region) is computed. If the neighbors intersect 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 constitutes input to the next iteration. This process continues until the entire image pixels have been assimilated into regions [21]. To eliminate the dependency on initial seeds and to make the method automatic statistical information and a priori knowledge can be incorporated in the algorithm. Region growing can be so sensitive to noise, that it may cause extracted regions to have holes or even is disconnected. Conversely, overlapping gray value distribution in MR images can cause separate regions to become connected.

Region growing is not often used alone because it is not sufficient to segment brain structures accurately and robustly. As compared to edge detection method, segmentation algorithms based on region are simpler and have strongly immune to noise [22], [23]. Edge method divide an image based on frequent changes in intensity near the edges, while, region method divide an image into regions which are similar as per a set of predetermined criteria [24].

3.3 Clustering Based Methods

The method of clustering organizes the objects into groups based on some feature, attribute and characteristic. Hence a cluster consists of groups of similar objects. There are two types of clustering, supervised and unsupervised. In supervised type clustering, cluster criteria are specified by the user. In unsupervised type, the cluster criteria are decided by the clustering system itself.

1) K-Means Clustering: K-Means Clustering partition the n observations into k clusters in which each pixel belongs to the clusters by minimizing an objective function in a way that the within cluster sum of squares is get minimized. It starts with initial K cluster centres and it reassigns the observations to clusters based on the similarity between the observations and cluster centre. Automation of detection and segmentation of brain tumors in MRI images is a very challenging task due to occurrence of high degree of gray-level similarity in the image. T. U. Paul and S. K. Bandhyopadhyay [25] have presented a fully automated two-step segmentation process of brain MRI images. In the first step, skull stripping is performed by generating a skull mask from the MRI image and in the second step, an advanced K-means algorithm improvised by two-level granularity oriented grid based localization process based on standard local deviation is used to segment the image into gray matter, white matter and tumor region and then length and breadth of the tumor is assessed.

2) Fuzzy C-Means Clustering: Fuzzy C-means (FCM) clustering is a data clustering method in which each data point belongs to a cluster to a degree specified by a membership value. Fuzzy C-means divides a collection of n vectors into c fuzzy groups and finds a cluster centre in each group such that a cost function of dissimilarity measure is minimized.

3.4 Edge Detection Based Methods

Edge-based methods are focused 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 considered as a very good 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.

Edge detection based scheme provides an efficient 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 that can move under the influence 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 includes: snake model, balloon model, gradient vector field snake, and level set approaches [26]. However, these approaches have a limitation of getting stuck at local minima and also highly sensitive to starting point.

3.5 Fuzzy Based Methods

Fuzzy logic is a set of mathematical principles for knowledge representation based on degrees of classical binary logic. In brain tumor segmentation fuzzy systems allow for the development of methods to perform the tasks related to intelligent human behaviours.

Dunn suggested image segmentation using fuzzy c-means (FCM) clustering algorithm [27]. FCM implemented by several researchers and provide improved version for segmentation for brain MRI. To overcome the intensity inhomogeneities in FCM, Arakeri et al. [28] proposed a modified version MFCM. Accuracy is one of the important factors for brain image segmentation applications, they preferred computational techniques. MFCM is applied to the approximate image to segment the tumor and contain more detail of the images.

Rajendran proposed fuzzy logic processing using c-means clustering on MR images for brain tumor segmentation [29]. FCM algorithm fails to deal with significant properties of images, which leads to strong noise sensitivity. To overcome this weakness, proposed a new clustering algorithm named PCM. Possibilistic membership, are very sensitive to the choice of the additional parameters of PCM, which directly decide the clustering accuracy.

To overcome the weakness of the original PCM algorithm combined the objective function of PCM and FCM into a new objective function and PFCM, which can be interpreted as PCM and FCM, respectively, in some special cases where some proper parameter were adopted Xuan ji et al. [30], [31]. Pal et al. [32] Proposed EPFCM method, distance metric in PCFM is modified in such a way that includes memberships, both local non local spatial neighbourhood information to overcome the noise effect in MRI brain medical images.

3.6 Atlas- Guided Approaches

Atlas-guided approaches are a powerful tool for medical-image segmentation when a standard atlas or template is available. The atlas is generated by compiling information on the anatomy that requires segmenting. This atlas is then used as a reference frame for segmenting new images. Conceptually, atlas-guided approaches are similar to classifiers except that they are implemented in the spatial domain of the image rather than in a feature space. Atlas-guided approaches have been applied mainly in MR brain imaging for segmentation of various structures, as well as for extracting the brain volume from head scans.

The standard atlas-guided approach treats segmentation as a registration problem. It first finds a one-to-one transformation that maps a pre-segmented atlas image to the target image that requires segmenting. This process is often referred to as 'atlas warping'. The warping can be performed with linear transformations, but, because of anatomical variability, a sequential application of linear and nonlinear transformations is often used [33]. Because the atlas is already segmented, all structural information is transferred to the target image. A major challenge associated with atlas-based segmentation techniques is developing the atlas itself. The atlas-guided approaches are generally better suited for segmentation of structures that are stable over the population of study [34].

3.7 Comparison of Segmentation Methods

In this study, we have studied different techniques for segmentation. The segmentation methods studied in this paper include thresholding, region growing, edge detection, clustering, fuzzy & atlas- based methods. Comparison of the studied techniques is shown in Table 1.

3.8 Papers Reviewed

S. Shen, et al, 2003, proposed [50] a new brain tumor diagnostic procedure using magnetic-resonance imaging (MRI) which circumvents the requirement of an invasive biopsy. In this method MR images were preprocessed, using standardizing, non-brain removal and enhancement and an improved fuzzy clustering algorithm was then applied to segment the brain MRI into different tissues. To complete the diagnosis fuzzy logic based genetic programming (GP) procedure was developed to search for classification rules. Classification results for three types of tumors on different MR images for different pathologies, indicated that the technique is promising.

TABLE 1. Summary Table of Segmentation Methods

Segmentation Method	Advantages	Disadvantages
Threshold-based: Global and Local Thresholding	Simple and computationally fast.	Limited applicability to enhancing tumor areas [35].
Region-based: Region-growing	Simple and capable of correctly segmenting regions that have similar properties and generating connected region [36].	Partial volume effect [37], [38]. Noise or variation of intensity may result in holes or over-segmentation.
Edge Detection Based Method	Focused on detecting contour. In vision based analysis, edge is considered as a very good descriptor of contrast [26].	Fail when the image is blurry or too complex to identify a given border. Inability to produce a reasonable solution in cluttered background.
Watershed	Segments multiple regions at the same time, produces a complete contour of the images and avoids the need for any kind of contour joining [39].	Over-segmentation [40].
Pixel-based: Fuzzy C Means	Unsupervised, always converges the boundaries of tumor.	Long computational time, sensitive to noise [41].
Artificial Neural Networks	Ability to model non-trivial distributions and non-linear dependencies [42].	Gathering training samples is not straight-forward and learning phase is slow [43].
Markov Random Fields	Are able to represent complex dependencies among data instances [44].	Difficulty when selecting the parameters that control the strength of spatial interactions, & usually require algorithms that are computationally intensive [45].
Model-based: Parametric Deformable Models	Capable of accommodating to the variability of biological structures over time and across different individuals [46].	The model may converge to wrong boundaries in case of inhomogeneities [47].
Level Sets Approach	Topological changes are naturally possible [48].	Computationally expensive [49].
Atlas- Guided Approach	Labels are transferred as well as the segmentation. They also provide a standard system for studying morphological properties, and the data from such study can be used to generate morphological statistics [34].	Developing the atlas itself is difficult.

M. C. de Andrade, 2004, introduced [51] an interactive algorithm for image smoothing and segmentation. This method combines some known image smoothing and segmentation methods of mathematical morphology and PDE-based level set frames. The segmentation was a region growing and automatically detect all image minima using a property inherited from the watershed transformation (NHW). A merging mechanism was used to change the image topology which reduces over-segmentation and the need of preprocessing. Accurate and fast segmentation results were achieved for gray and color images in any number of dimensions using this method.

Cigdem Demir, et al, 2005, presented [52] a graph-based representation (a.k.a., cellgraph) of histopathological images for automated cancer diagnosis by probabilistically assigning a link between a pair of cells (or cell clusters). First, the work defined a set of global metrics on a cell-graph to capture tissue level information coded into the histopathological images. Second, the results were obtained on the photomicrographs of 646 archival brain biopsy samples of 60 different patients by comparing the cell-graph approach against cell-distribution and textural approaches for tissue level diagnosis of brain cancer called malignant glioma. This method measured the strength of the cell-graph representation which showed 99 percent accuracy for healthy tissues with lower cellular density level, and at least 92 percent accuracy for benign tissues in the diagnosis of cancer.

Carles Arus, et al, 2006, introduced [53] HealthAgents, an EC-funded research project to improve the classification of brain tumors through combination of vivo MRS with in vitro MAS and gene expression. HealthAgents solved the problem of collection and management of highly complex data by building multi-agent

decision support over a distributed network of local databases or data marts. They introduced a unique technology to develop clinical tools for the diagnosis, management and understanding of brain tumors.

G. Farias, et al, 2008, proposed [54] a synergy of signal processing techniques and intelligent strategies was applied in order to identify different types of human brain tumors, so that it help to confirm the histological diagnosis. The wavelet-SVM (support vector machine) classifier merged wavelet transform and SVM to reduce the size of the biomedical spectra and to extract the main features, with SVM to classify them. It reduces the classification time and improve the results specially taking into account that medical knowledge was not considered.

Rajeev Ratan, Sanjay Sharma, S. K. Sharma, 2009, have developed [55] a brain tumor segmentation method on 2D MRI Data which automatically identifies tumor tissue. The watershed segmentation method did not require any initialization inside the tumor and the visualization and quantitative evaluations of the segmentation results demonstrate the effectiveness of this approach. This method performance is better for the cases where the intensity level difference between the tumor and non tumor regions is higher.

Sabuncu et al, 2010, proposed [56] a nonparametric, probabilistic model for the automatic segmentation of medical images, given a training set of images and corresponding label maps. Label fusion segmentation approach can be employed on large multi-subject datasets and yields more accurate segmentation than FreeSurfer's widely used atlas-based segmentation tool and previous label fusion algorithms. It robustly detected hippocampal volume differences in a study of early Alzheimer's Disease and aging.

Debnath Bhattacharyya and Tai-hoon Kim, 2011, proposed [57] an image segmentation method to indentify or detect tumor from the brain magnetic resonance imaging (MRI) for further consideration of medical practitioners. Thresholding methods have different result in each image. So a set of image segmentation algorithms was proposed by which detection of tumor can be done uniquely on brain tumor images.

In contrast to segmentation algorithms, detection algorithms only try to decide if tumor is present and output the approximate tumor location instead of providing a complete segmentation. The tumor detection could be used for initializing a segmentation method. Saha et al, 2011, proposed [58] a method to locate the tumor using a fast unsupervised change detection method searching for dissimilar regions across the symmetry line of the brain using Bhattacharya coefficient score. This method drew a bounding box, instead of segmenting tumor which helps in quick analysis of large amounts of data.

Farjam et al, 2012, proposed [59] a template-matching method to detect metastases on conventional MRI for screening purposes. The result was improved on the spherical template generation process by varying tumor size, lesion shape and intensities to achieve more accurate detection rates.

The most common way to quantitatively evaluate segmentation results is to calculate the overlap with the ground truth. Usually, Dice similarity coefficient (DSC) or Hausdroff Distance are used. DSC can range from 0 to 1 with 0 indicating no overlap and 1 indicating perfect overlap. Another method is to assess results on a synthetic dataset including ground-truth. Although synthetic data lacks important characteristics of real images, it has been used by many groups for initially assessing both segmentation and registration methods on healthy datasets.

Zou et al, 2004, compared [60] the three different validation metrics: area under the receiver operating characteristics (ROC) curve, mutual information (MI) and Dice similarity coefficient (DSC) for probabilistic brain tumor segmentation. The conclusion was that for overall classification accuracy the area under the ROC curve should be used, for sensitivity to changes in tumor size MI was the metric of choice and for spatial alignment evaluation the Dice coefficient was best.

IV. Conclusion

Image segmentation is extensively used in numerous biomedical-imaging applications, e.g., the quantification of tissue volumes, study of anatomical structure, diagnosis, localization of pathology, treatment planning and computer-integrated surgery. Now-e-days, speed of computation is no longer an issue for researchers. Therefore, the focus is directed toward improvement of information from images obtained through the slice orientation and perfecting the process of segmentation to get an accurate picture of the brain tumor. As diagnosing tumor is a complicated and sensitive task; therefore, accuracy and reliability are always assigned much importance. Hence, an elaborated methodology that highlights new vistas for developing more robust image segmentation technique is much sought.

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