

Graph Based Brain Network Structure and Brain MRI Segmentation Techniques



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Abstract: Graph based representation of medical images is very challenging task due to complexity of various images taken using different techniques like MRI, Ultrasound, CT scan and PET scan. Graph theory provides simplified notations and tools in order to representation Brain network structure. The brain network structure helps to analyze and detect brain tumor because it is structurally and functionally organized complex system. Brain network structure and functional analysis using graph based techniques have been successfully used in various types images and medical data analysis. Simplified representation of brain structure plays a crucial role in analysis and detection of brain related diseases. Because various kinds brain tumor types allows to have different images and brain tumor analysis is one of the most significant challenges. This paper also represents graph theory based brain tumor detection and classification steps using hybrid Fuzzy C-Means technique. Segmentation error may increase due to presence of noise, intensity variations, interclass values in manual segmentation. To avoid this, use automatic segmentation which gives better results for clinical analysis of MRI images. In this paper different types brain tumors, Graph based analysis of complex Brain Structure, various brain tumor segmentation and detection techniques using MRI and its merits and demerits are surveyed and summarized. We also discussed future research directions in analysis of MR Images and some challenging issues of brain tumor evolving in medical research field.

Keywords: Graph theory, Magnetic resonance images, Brain network Structure, Fuzzy C-Means.

I. INTRODUCTION

Brain tumor is abnormal growth of cancerous cell inside and around the brain. Mainly there are two types brain tumor called primary and secondary types. In primary, cancerous cell start growing inside the brain area where as in secondary cancerous cell start growing in any parts of the body and finally effecting to the brain. Graph theory based representation of brain network structure helps to analyze in detail the structural and functional characteristic of Brain tissues. So that any change in this normal structure and functions of brain tumor may leads some brain related diseases. Because of known structure of brain network, any change in brain functions and structure can be easily diagnosed in clinical therapy. According to World Health Organization [1]

cells and benign are non cancerous cells. Whether primary or secondary tumor type, if it is grade IV stage it is very difficult recover and it is life threatening leads death. The low grade tumors are Meningiomas and Gliomas are, classified as benign tumors. The high-grade tumors are Glioblastoma and Astrocytomas are, classified as malignant tumors. The brief summary of brain tumor types, location and symptoms [5] are given in Table1. According to the World Health Organization, brain stroke and brain tumor are considered most dangerous diseases that cause of more death across the world as compare to heart diseases. According to survey in India, every year 50,000–60,000 persons are suffering with a brain tumor[2]. Various types of tumor are exist, each having different location, characteristics and symptoms, because of this it leads complexity and challenging task to detect the tumor using MRI images even with availability of various kinds technologies in medical field. MRI technique works on using a strong magnet filed and radiofrequency (RF) waves to provide neat, exact and detailed representations of internal body structures and tissues. Along with this MRI scan, there are other techniques like CT scan, ultrasound, PET scan also gives images of brain for clinical study for diagnosis.

the brain tumors are classified as four grades from I to IV, this grades states the severity of the brain tumor diseases namely Grade I is starting stage and less harmful and Grad I IV is last stage and more harmful.. Recovering from Grade IV stage is very difficult it may leads death in most of the cases. Tumor cells would be malignant or benign. Malignant are cancerous

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Table.1 Types of Brain Tumor with Location and Symptoms

Tumor type	Location	Symptoms
Acoustic Neuroma	Nerve fibers	Hearing loss in one ear, Dizziness or vertigo Tinnitus (ringing in the ear) Tingling or numbness in the face
Astrocytoma: <ul style="list-style-type: none"> Grade I – Pilocytic Astrocytoma Grade II – Low-grade Astrocytoma Grade III – Anaplastic Astrocytoma Grade IV – Glioblastoma 	Brain stem and cerebellum other parts of the CNS	Speech or balance abnormalities Difficulty swallowing Fatigue and sleepiness Problems with coordination Neck pain or stiffness Seizures Weakness or paralysis Nausea and vomiting
Chordoma	Sacrum, near the lower tip of the spine,	Double vision Headaches
CNS Lymphoma	Central nervous system	Headaches, Seizures Partial paralysis on one side of the body Cognitive or speech disorders
Craniopharyngioma	The parasellar region	Visual changes, Weight gain Delayed development in children
Other Gliomas: <ul style="list-style-type: none"> Brain Stem Glioma Ependymoma Mixed Glioma Optic Nerve Glioma Subependymoma 	Area of the Brain, near the nerve pathways between the eyes and the brain, fourth and lateral ventricles	Headaches, Speech or balance abnormalities Difficulty swallowing Fatigue and sleepiness Problems with coordination Neck pain or stiffness Weakness or paralysis
Medulloblastoma	Cerebellum or near the brain stem	Early morning vomiting, Lethargy or sleepiness Lack of coordination Double vision
Meningioma	Brain and spinal cord.	Seizures, Nausea and vomiting, Vision changes
Metastatic Brain Tumors	Cerebellum or brain stem	Seizures, Headaches Behavioral and cognitive changes
Oligodendroglioma	Frontal or temporal lobes	Headaches, Behavioral and cognitive changes Weakness or paralysis
Pituitary Tumors	Near the pituitary gland,	Behavioral and cognitive changes Cessation of menstrual periods (amenorrhea) Hair growth in women
Primitive Neuroectodermal (PNET)	CNS	Nausea and vomiting, Seizures Unusual sleepiness or lethargy Behavioral or personality changes Unexplained weight loss or weight gain
Schwannoma	Around nerve fibers	Balance problems Deficits depend on the nerve that is affected

II. TYPICAL METHOD OF BRAIN TUMOR ANALYSIS USING MRI

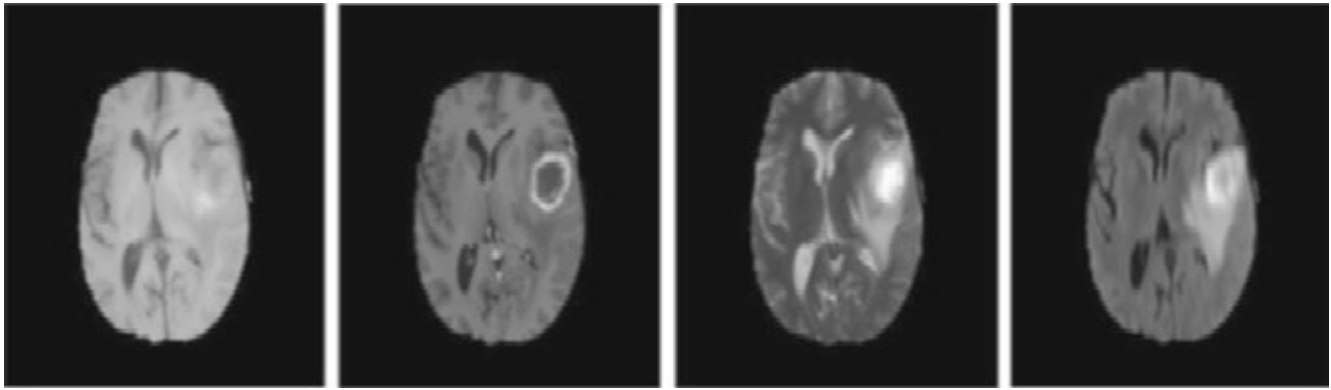


Fig.1 Using BRATS 2013 data [8] Brain tumor modalities like T1w, T2w, T1C, FLAIR taken respectively.

In MRI scans we identify four sequences, namely T1 – weighted (T1w), T2 – weighted (T2w), T1 – post-contrast (T1C), and Fluid Attenuated Inversion Recovery (FLAIR). T1w and T1C, tumor are low grade tumor type with hypo-intensity. T2w and FLAIR are high grade tumor type with hyper-intensity [23]. Generally, T2w images are considered in clinical diagnose to treat brain tumor and over come from this disease.

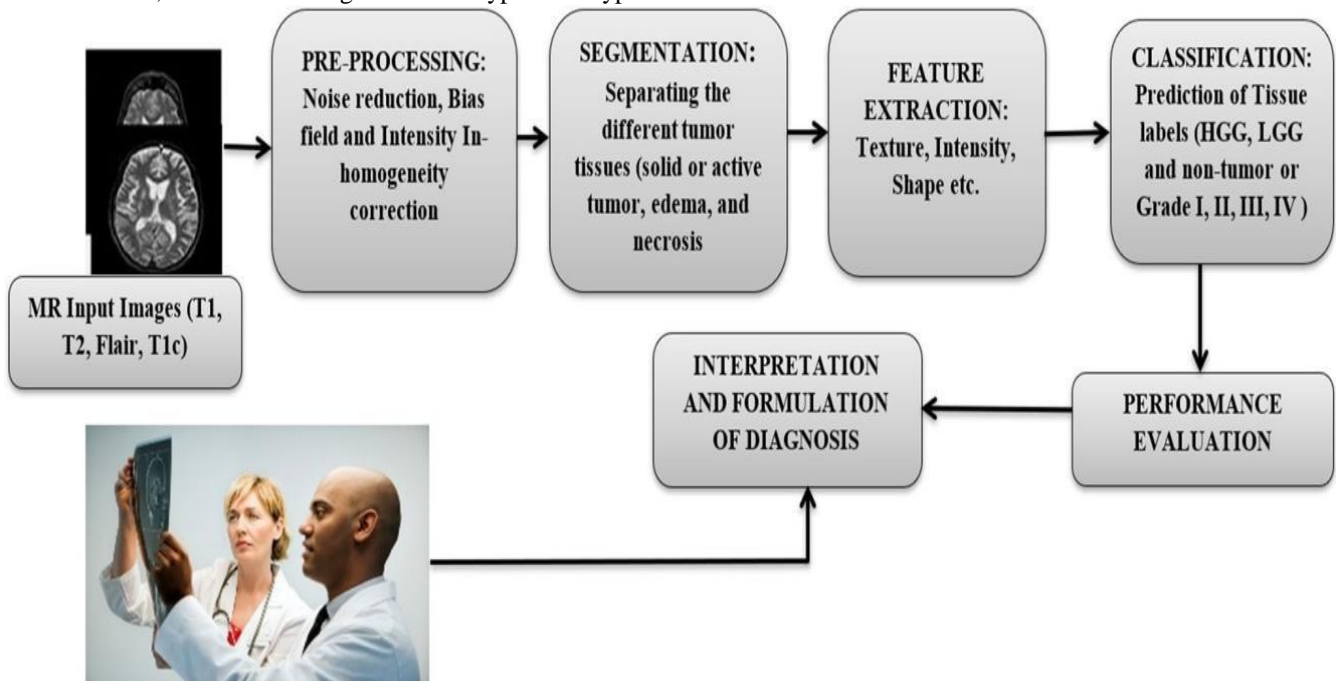


Fig.2 Typical Methodology of MRI Brain Tumor Analysis.

In adults the most common brain tumor type is Gliomas and it can be seen by magnetic resonance imaging (MRI) with various sequences, such as T1-weighted (T1), T1-weighted contrast-enhanced (T1c), fluid-attenuated inversion recovery (Flair) and T2-weighted (T2). Figure 1 shows Gliomas type taken from MRI different sequences with respect to four grades of brain tumor obtained from BRATS 2013 dataset. In medical image research analysis any medical images usually comprise of various steps namely pre-processing, image acquisition, image segmentation, feature extraction and classification. Brain tumor analysis also commonly use general image processing steps for proper segmentation result so that this research result can be used in diagnosis and treating brain tumor patients in hospitals. The malignant brain tumor type called gliomas are segmenting is very difficult and as well challenging task because of the of following issues identified with respect to this grade of MRI scans: (1) In

gliomas has blurry and unclear borders because of invade the neighboring (2) varied size, shape, and appearance of gliomas appear in any parts of brain tissue (3) MRI data has intensity variations increases the difficulty of image segmentation and (4) brain tumor tissue with T1w modality results bright intensity in effective tumor tissue. Tumor cells have varied intensity depends on parts of brain white matter and other tissues matter. While tumor boarder identification using some graph cut techniques measures the intensity level of tumor area and around tumor tissue. Preprocessing is first step in automated detection of a brain tumor in MR images and it is also crucial step in every medical image. Various kinds like noises, intensity variations and skull stripping are removed by using image enhancement techniques. Intensity Variations is due to use

different magnetic field in MRI machines. This can be corrected by using Bias-Field Correction method. Interclass variability is due to varied tissue matter measured with different parts of brain during MRI scan. This can be processed using image normalization algorithms. Figure 2 illustrates the different steps of MRI brain tumor analysis, further steps like classification, interpretation; evaluation and formulation of disease diagnosis are performed later after segmentation of MRI images. A brief study can be done to extract tumor position features for further classification to identify specific tumor type by comparing the last 10 years data. After preprocessing Segmentation is the very challenging task even a lot of research has done using different techniques. Segmentation is a process of dividing an MR image into small segments for another representation of image makes further processing of image easier. One method called hybrid Fuzzy C-means algorithm performs segmentation using graph cut techniques. In this algorithm, the user interaction (data points/user scribble/marks) are selected as centroid points for Fuzzy C-mean clustering method; they are seed selection points for cluster membership. FMSS technique is employed to improve the accuracy of selection of the seed points in lesser time. FMSS is employed to obtain effective centroid points for segmentation. After segmentation next step is to transfer image into set feature, this process is called feature extraction. Feature extraction is to extract and measure part of segmented image based on its characteristics. Classification is the process of organization of the data based on their features extracted, which is a necessary for categorize tumors grading.

III. GRAPH BASED ANALYSIS OF COMPLEX BRAIN NETWORK

Discrete and mathematically simple representation that lends itself well to the development of efficient and provably correct methods. Graph based method have proven to be a useful tool in wide variety of energy minimization problem. Ability in reflecting global image properties. A minimalistic image representation. Flexibility in representing different types of images. Graph is simple model of complex structures, define as a set of nodes and edges which can be represented as $G = (V, E)$ (Fig.3). This method have become a great tool in the field of technological, biological and amusing sciences such as the science of ecological networks, the World Wide Web, amusing networks and neuroscience. Onias *et al.* (2014) described that a network is a way to code a set of elements together with their connections. The elements are identified as nodes and their connections are identified as edges. When two nodes are connected by and edges, they are considered neighbors. In addition, edges can be categorized as directed, undirected and weighted (Fig.4 and Fig.6).

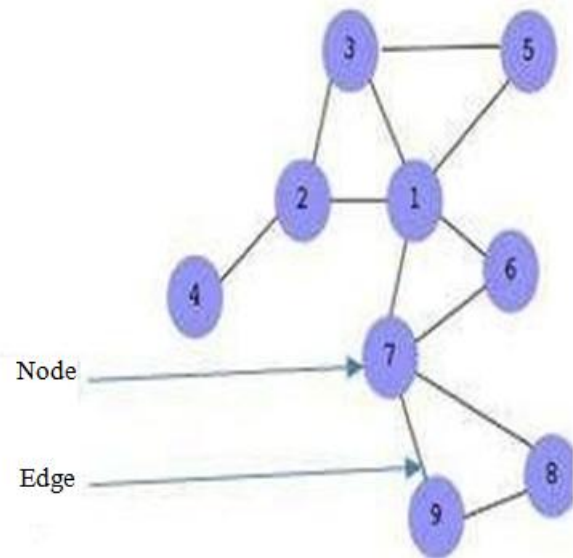


Fig.3 Graphical representation of Graph

Moreover, a network framework with N nodes is said to accept labels N that assigns a representation (weight) to each link is called weighted network. Otherwise, if the links of a network do not accept labels, the system is named unweighted network. As previously described, the brain can be seen as a complex network. The use of graph based technique in medical science of neurons has become great to measure brain functions in agreement of anomalous reconfiguration of brain networks. Besides, graph theory analysis of brain networks can be blindly activated to brain signals. The adversity with integrating data from multiple modalities is that it is computationally actual ambitious to analysis and it is acutely difficult to anticipate the relationships between objects in the data (Fallani *et al.*, 2014) networks can be blindly activated to brain signals. The adversity with integrating data from multiple modalities is that it is computationally actual ambitious to analysis and it is acutely difficult to anticipate the relationships between objects in the data (Fallani *et al.*, 2014).

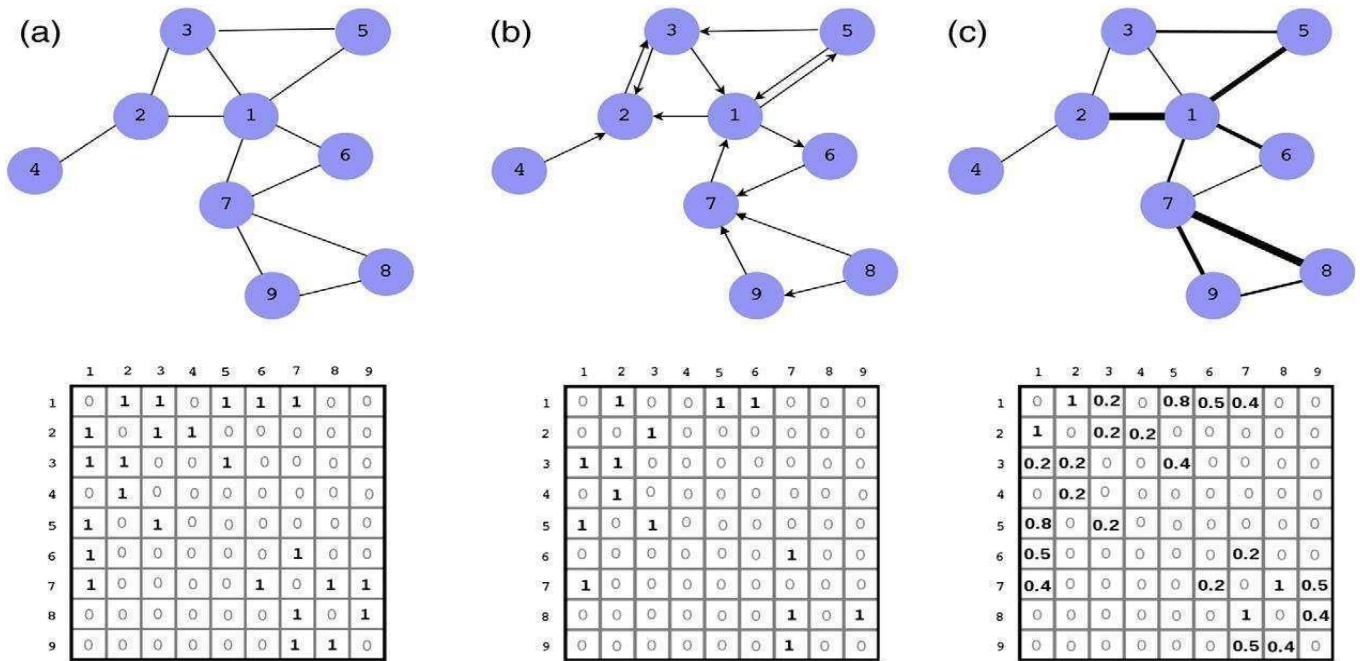


Fig.4 Examples of (a) Undirected, (b) Directed and (c) Weighted Networks (top row) and their corresponding adjacency matrices, coded with a gray-scale colour map (bottom row). Image courtesy of (Onias et al., 2014)[6]

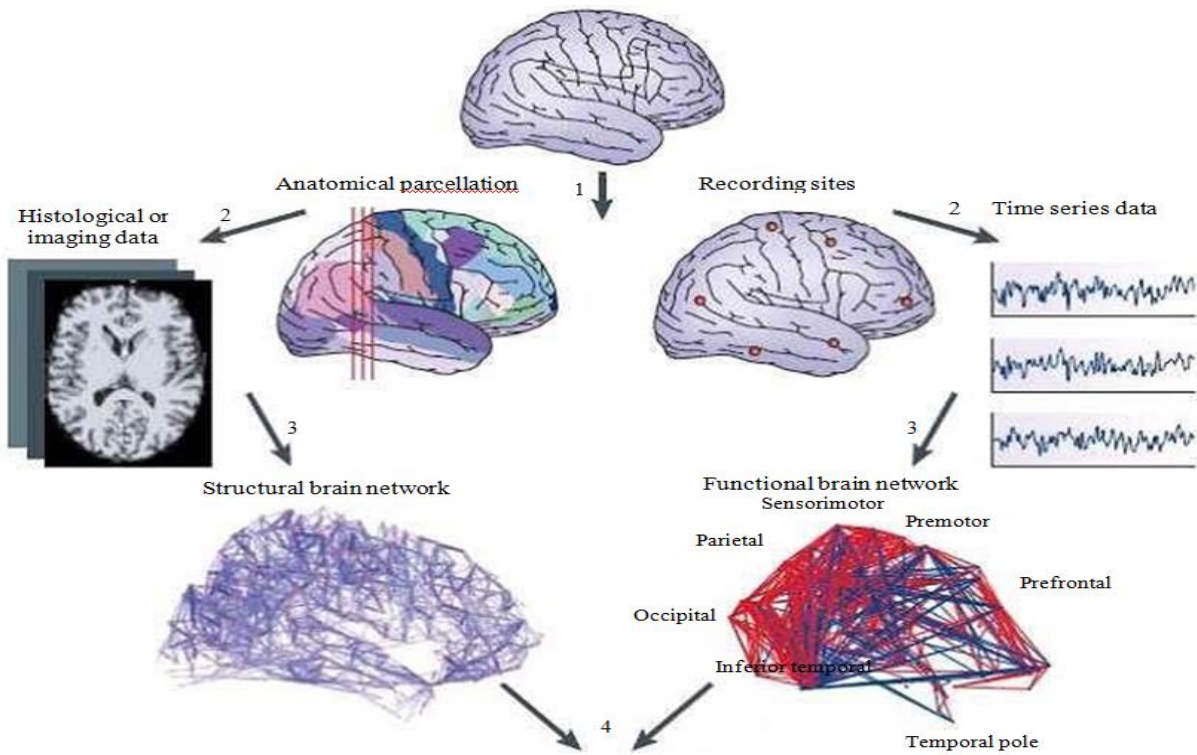


Fig. 5 Graph Theory Analysis of Functional and Structural Brain Network [6]

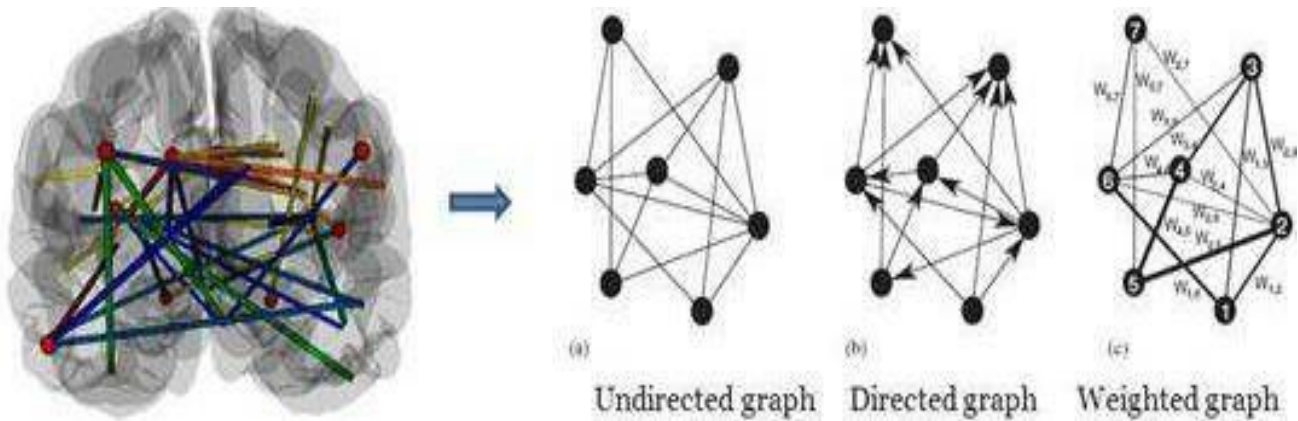


Fig.6 Examples of Complex brain Network based on Graph. Image courtesy of (Boccaletti et al., 2006; Fallani et al., 2014)[6]

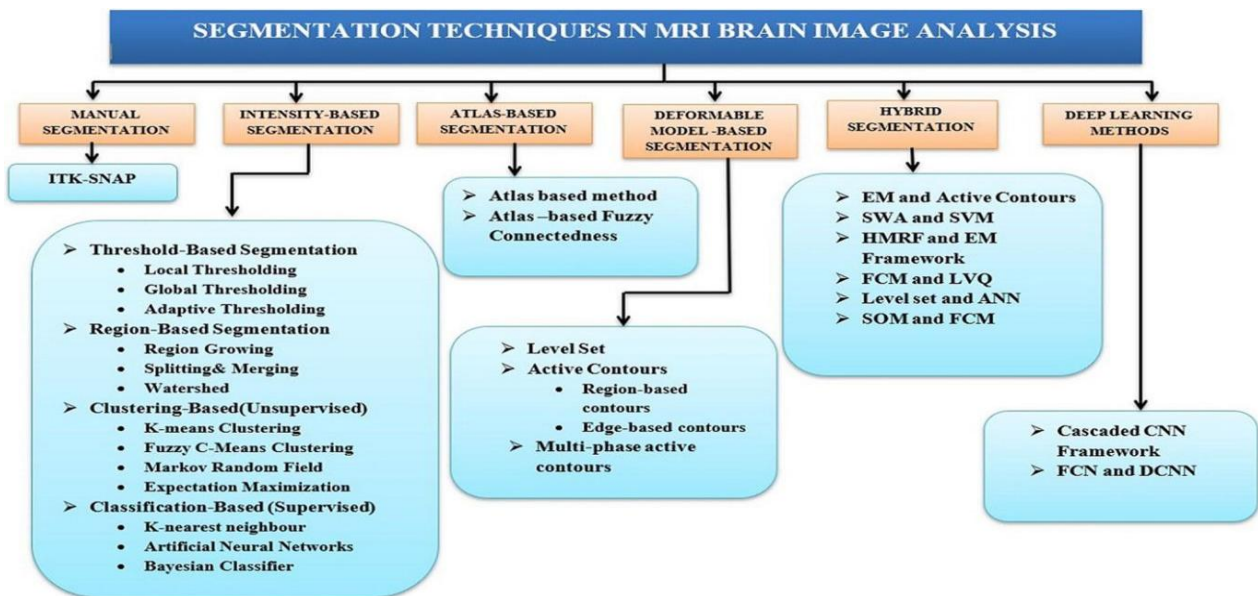


Fig.7 Image Segmentation Techniques and Sub-classification for Brain Tumor Detection

A) Brain Network Connectivity

The human brain is organized by structurally and functionally and it is one of the most complex systems. Brain connectivity may be analyzed and considered application as a broad range of network analysis methods and categorized as: Structural connectivity and functional connectivity (Fig.5) (Ciric et al., 2016). Many of the brain connectivity methods are already activated in alongside efforts to map and call added biological systems, e.g., those of cellular metabolism, ecology or gene regulation. The approach of directed graphs is one of the most popular methods to map networks of structural and functional brain connectivity at all stages. Graphs are collection of nodes and edges which are corresponding to brain regions and pathways. In the easiest form, graphs can be declared by a connection matrix with binary elements that identify the existence or lack of a directed edge between pairs of nodes. Generally, nodes can connect with other nodes through indirectly or directly. Indirect interaction is a connection of multiple edges and the functional effectiveness of these indirect connections are depends on the path length of directed graph

1. Structural Brain Network Connectivity

Structural brain connectivity represents the structural associations a part of altered neuronal elements including both the morphometric alternation and accurate anatomical

connectivity. At the complex he structural connectivity of human brain *in vivo* can be completed by structural and diffusion MRI. (Bullmore and Sporns 2009; Van der Horn et al., 2017). Structural connectivity of this affectionate is anticipate to be almost abiding on under time scales (seconds to minutes) brain networks, this access about accredits to white amount projections bond cortical and subcortical regions. It only some of artificial experience-dependent variations at best time scales (hours to days) (Friston et al., 1993). In addition, in the field of neuroimaging, as the directionality of projections currently cannot be detected, the structural brain connectivity is mostly abstinent as a set of accidental relations.

2. Functional Brain Network Connectivity

Functional brain connectivity denotes the functional relations of brain areas accepting by quantifying the temporal correlations between spatially limited neurophysiologic contest from fMRI and EEG/MEG data (Friston et al., 1993; Kabbara et al., 2016b). It is largely derived from time series analysis of complex brain networks because it is highly time-dependent and describes patterns of statistical reliance among neural elements (nodes and edge) (Joo et al., 2016; Zhang et al., 2017). A various number of neuroimaging techniques, including diffusion MRI, functional MRI,



Electroencephalography (EEG), Magnetoencephalography (MEG) may be applied to analyze time series data of functional brain connectivity and can be figure out in a number of ways, including as spectral coherence, mutual information, or cross-correlation. First, establish the network nodes. Second, Estimate connected admeasurements of affiliation between nodes. In third, Generate a connection cast by accumulation all pairwise links between nodes. In fourth, analyze the parameters of brain networks. Image courtesy of (Bullmore and Sporns, 2009).

C) The future indications of functional brain connectivity is to apply an algorithm in time-evolving graphs, where the challenging factors are to extract features and to find patterns incrementally over time. Another indication of brain connectivity is if the functional brain connectivity features are extracted from the neuroimaging data, graph based techniques can be further applied to complex brain networks and examine their essential topological properties to detect abnormalities.

D) SEGMENTATION TECHNIQUES IN MRI BRAIN TUMOR ANALYSIS

$$R(L) = \sum_{p \in P} R_p(L_p)$$

E) Segmentation of medical images is a process of

$$B(L) = \sum_{\{p,q\} \in N} B_{\{p,q\}} \cdot \delta(L_p, L_q)$$

dividing pixels into set of smaller pixel segments. The aim this segmentation processes is detect and separate the targeted area in a given MRI images.

$$cut(o, b) = \sum_{p \in o, q \in b} w(p, q)$$



Fig.8 New

Proposed Method for Segmentation

The first step in medical image processing is pre-processing, where noises can be removed from images. The pre-processing of the input MRI image is carried out using three techniques

- RGB to grey conversion
- Skull strip removal
- Histogram equalization

After preprocessing, segmentation is carried out using Fuzzy C-Mean clustering by Seed Selection (FMSS) method. In this method, based on the user interaction (data points/user scribble/marks) centroid points for Fuzzy C-mean clustering selected, they are seed selection points for cluster membership. FMSS technique is effective centroid selection method to improve accuracy. The new method for brain MR images segmentation shown in Figure.8.

A) Energy function

The proposed method for brain tumor segmentation uses graph cut techniques. In this research work we have used energy function given by Penget.l, Cost function E(L) is defined as follows:

$$E(L) = \gamma R(L) + B(L)$$

Where, L= {l1, l2,...lp}, is a vector which gives label 0 for region term and 1 for boundary term.

$$L = \sum_{k=1}^n l(k)$$

A) Region and Boundary term

B) Region term: Regional energy cost R(L) which is generated between the terminal nodes and pixels . R(L) represents the global region cost term, whichequals to the sum of each pixel's cost.

C)

D) □ Boundary term: Boundary energy cost function B(L) which is generated between the two belongs to object and back ground pixels. B(L) represents the global boundary cost term, which the cost between the neighbour pixels.

E)

F) Graph Cut

G) The minimum cut on the nodes in the graph is performed; where intensity of the neighboring pixel in the graph is similar, but different cost labels. So, graph cut with cost energy function is performed, whose value is given in below equationWhere, o is foreground label, b is back ground label and (p,q) are the adjacent pixels belonging to the object of interest.

H) Even though variety of brain tumors, still it is a challenging task because of the difficult structure of brain network and different characteristics of tumor in the MR images [21]. Table.2 Shows various segmentation techniques and results. Lot of research has been done in this area i.e detection of brain tumor using MRI over many years. All this techniques can be divided into six classes: Manual segmentation, intensity-based techniques, atlas-based methods, deformable model based techniques, hybrid segmentation methods. and deep learning methods[22]. Figure.7 Summarizes the various segmentation techniques.

Table.2 Segmentation Techniques and Results.

Author	Year	Paper Name	Technique	Result
D. N. Louis	2007	The 2007 WHO classification of tumors of the central nervous system	Detection of CNS(Central Nervous System)	The molecular parameter is used for its diagnosis structure.
D. J. Hemanth	2009	"Effective Fuzzy Clustering Algorithm for Abnormal MR Brain Image Segmentation	Abnormal MR Brain Image Segmentation	It gives abnormal MR image segmentation accurate region of cancer and better identification of branch i.e. stage of cancer.
A. A. Abdullah	2012	Implementation of an improved cellular neural network algorithm for brain tumor detection	Neural network	It solves high complex problem and it is used to map an input into a desired output.
I. Maiti and M. Chakraborty	2012	A new method for brain tumor segmentation based on watershed and edge detection algorithms in HSV color model	watershed and edge detection algorithms in HSV color model	It gives color brain MRI image for very good accuracy result.
S. Charutha and M. J. Jayashree	2014	An efficient brain tumor detection by integrating modified texture based region growing and cellular automata edge detection	Automated and efficient brain tumor detection	The proposed method efficient in treatment of brain tumor and also in removal of tumor.
T.Kalaiselvi, P.Nagaraja and P.Sriramakrishnan	2016	Brain tumor detection using Image processing and sending tumor information over GSM	K-Mean and Fuzzy C Mean	Results in distorted boundaries and edges.
Rajeev Kumar ,Dr. K. James Mathai	2016	A Simple image processing approach to abnormal slices detection from MRI tumor	Fuzzy Symmetric measures	It takes minimum missed alarms.
Arbaz Mukaram Chidananda Murthy.M.V, M.Z.Kurian	2017	Brain Tumor Segmentation by Modified K-Mean with Morphological Operations	Morphological Operators and K-mean	Not work for global cluster.
Sumathi N, Kreethi P	2017	Efficient image segmentation of brain tumor detection using fuzzy c-mean and mean-shift	Fuzzy c-mean and mean-shift	Neglected the use of fuzzy and region growing segmentation.
R Sharmila*1, K Suresh Joseph2	2018	Brain tumor detection of MR Image Using Naïve Beyer Classifier and Support Vector Machine	SVM and Naïve Bayes algorithms	It shows accuracy of 91% with SVM classification algorithm but they used only 110 brain images as dataset.

III. FUTURE RESEARCH DIRECTIONS

In the field of neuroscience, Graph-theory analysis of brain network is one of the complex task. Although many researchers already engaged with this research field still there are some challenging issues got to be identified. Complex brain network analysis b used on the graph might be both useful and feasible for more profound studies but still required for more systematic assessment. Besides, in complex brain networks, there are deficiencies of a gold standard for the meaning and descriptions of network nodes and edges or links. Ensuring the suitable use of network analysis, researchers still have to need to take attention

When choosing the right network demonstration of the brain connectivity. The most prominent area of expansion is, structural brain connectivity had modeled for structural associations among different neuronal elements derived from resting f MRI and functional brain connectivity had modeled for the functional associations among brain regions measured with diffusion MRI but nobody tried for the whole-brain network. So, the combination of both structural and functional connectivity can be modeled as networks with different neuro imaging modalities.

Imaging techniques of the future will provide integrative evidence to map the patterns of whole brain connectivity.

IV. CONCLUSION

Analysis of medical images is been very much important in the medical field in all aspects. In this modern era, we have to adopt new technique of medical world, in order to treat the patients in effective with better results. Complex brain structure is defined both in structural and functional aspects, helps in analysis of various brain diseases, In this survey paper, various brain tumor types its advantages and disadvantages, and brain network structure are brief outdid. Also proposed new hybrid method called graph theory based image segmentation using FCM and graph cut techniques. This method is performs automated segmentation for better performance evaluation. Ultimate objective of this paper is to find new techniques for MR images analysis and detection of brain tumor by overcoming all the disadvantages of the previous techniques and also focuses on the future directions in graph based medical images analysis.

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