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A Study of Brain Tumor Detection Techniques

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***Abstract*— The brain tumor detection is a critical application of medical image processing. The literature survey shows that the most of the methods which are existing have ignored the images which are of poor quality i.e. with noise and low brightness. Moreover most of the existing work has neglected the use of object based segmentation. The overall goal with this research work is to get the short comings in earlier brain tumor detection techniques and get the possible solutions for the same. This paper ultimately ends up with the suitable future directions to increase this work.**

***Keywords*— Brain Tumor, Segmentation, Region growing, Active Contours, Neural network**

I. INTRODUCTION

Image segmentation is the procedure of partitioning a digital image into multiple segments (sets of pixels, also referred to as super-pixels). The target of segmentation would be to change or simplify the representation of a graphic into something that's more meaningful and better to analyze. Image segmentation is usually used to locate objects and boundaries in images. Precisely, the segmentation of image is the procedure of assigning a name to every pixel in a graphic in ways that pixels with the exact same label share certain visual characteristics.

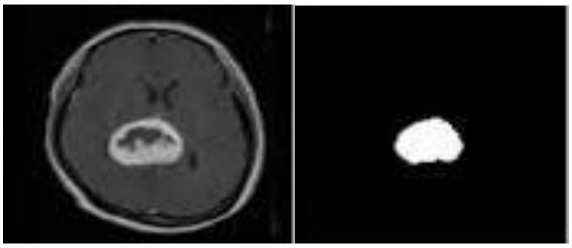

Fig. 1 left: original image, right: Segmented image

MRI Images of brain tumor cannot exactly denote the position of brain tumor, so to acquire the precise position of tumor in the MRI image pre-processing, segmentation; morphological operation and subtraction are used. This provides the precise shape of the tumor for the reason that MRI image and finally detection of brain tumor in MRI images is achieved. The consequence of image segmentation is an accumulation of segments that collectively cover entire image, or perhaps a set of contours extracted from the graphic. Most of the pixels in an area resemble for much characteristic or computed property, including colour, intensity, or texture. Adjacent regions are significantly different dependent upon exactly the same characteristic(s). When placed on stack bits of images, typical in medical imaging, the resulting contours after image segmentation enables to create 3D reconstructions with assistance from interpolation algorithms like matching cubes.

II. BRAIN TUMOR

A brain tumor is an intracranial solid neoplasm, a tumor (defined as an abnormal growth and development of cells) within the brain or possibly the central canal. Some tumours are brain cancers. Brain tumors include all tumors inside the human skull (cranium) or even in the central spinal canal. They may be assembled by an abnormal and uncontrolled cell division usually in the mind itself, but in lymphatic tissue, in arteries, in the cranial nerves, in the mind envelopes (meninges), skull, pituitary gland, or gland. From the mind itself, the involved cells may be neurons or glial cells (it includes astrocytes, oligodendrocytes and ependymal cells). Brain tumors might also spread from cancers primarily located in other organs (metastatic tumors).

Brain tumor is very serious and life-threatening for the invasive and infiltrative character in the limited space of intracranial cavity. Brain tumors won't be invariably fatal, especially lipomas which were inherently benign. Brain tumors can be malignant (cancerous) or benign (non-cancerous); however, the definitions of such neoplasm's differs from those commonly contained in other forms of non-cancerous or cancerous neoplasm's in the body. Its threat level depends mostly on the mixture of factors such as for example for instance just about any tumor, its location, its size and state of development. Because the brain is well protected by the skull, earlier detection of brain tumor occurs provided diagnostic tools are inclined to the intracranial cavity. Most of the times, detection occurs in advanced stages once the utilization of the tumor is responsible for unexplained symptoms.

Primary (true) brain tumors are normally positioned in the posterior cramial fossa in children and within the anterior two-thirds of the cerebral hemispheres in adults, although they could affect any type of the brain. Visibility of symptoms of brain tumors mainly utilizes two factors: the tumor size (volume) and tumor location. The moment that symptoms may become apparent, either to whomever or people around her or him (symptom onset) is usually a landmark through the entire verification and treatment with the tumor. The symptom onset – within the timeline of the creation of the neoplasm – is based mostly on many occasions, on the with the tumor but on many occasions can also be related to the modification with the neoplasm from "benign" (*i.e.* slow-growing/late symptom onset) to more malignant (fast growing/early symptom onset).
Tumors can be benign or malignant, could happen around as their pharmaceutical counterpart, and may or might not be primary tumors. A principal tumor is one that has pointed in the brain, rather than a metastatic tumor, that's something who has spread towards the brain from another part of the body. The metastatic tumors tend to be prevalent than primary tumors by 4:1. Tumors may or may not be symptomatic: some tumors are discovered because patient has symptoms, others appear incidentally by having an imaging scan, or at an autopsy.

III. BRAIN TUMOR DETECTION TECHNIQUES

There are four main techniques for brain tumor detection as given follows:

A. Tumor detection using Active Contour

The way will be based on active contours evolving eventually in accordance with intrinsic geometric measures of the image. The contours which evolves will split and merge, allowing the detection of varied objects simultaneously and both interior and exterior of the boundaries. This technique is using the relation between active contours combined with computation of geodesics or minimal distance curves. This geodesic means for object segmentation allows connecting classical "snakes" determined by energy minimization and geometric active contours using the theory of curve evolution. Experimental outcomes of application the scheme to real images including objects with holes and medical data imagery demonstrate its power. Moreover, consequences may be extended to 3D object segmentation as well.

B. Based on Region Growing

Region growing is just a simple region-based image segmentation method. It can be classified as a pixel-based image segmentation method since it involves the decision of initial points. This process to segmentation examines neighbouring pixels of initial "seed points" and determines perhaps the pixel neighbours should be incorporated with the region. The process is iterated on, in the exact same manner as general data clustering algorithms.

$$\text{Initialseed} = (x_i, y_i) = \arg \min_{(x,y)} \left(|w(x,y) - \text{mean}_w|\right)$$

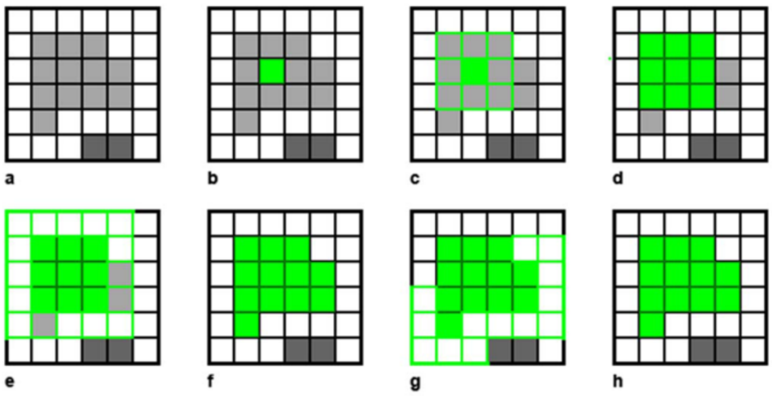

Fig 2.Principle of region growing segmentation

Fig 2 shows the algorithm principle. There are two objects in various gray shades (a).The green pixel indicates the seed point with the neighbouring pixels, as shown in (b) and (c) respectively. Fig 2 d shows their state after the first iteration, green pixels were put into the object. The ultimate segmentation result, after three iterations, is shown in (h).

C. Using neural network

Artificial neural networks (ANNs) are non-linear data driven self adaptive approach rather than the traditional model based methods. They're powerful tools for modelling, particularly when the underlying data relationship is unknown. A significant feature of such networks would be the adaptive nature, where "learning by example" replaces "programming" in solving problems. This feature makes such computational models very appealing in application domains where you've got little or incomplete understanding from the problem to be solved but where training data is readily available. The symmetry, texture features, intensity and shape deformation were improved in each image. The AdaBoost classifier was utilized to find the most discriminative features to have the ability to segment the brain tumor region. Moreover, Multi-modal MR images with tumor are utilized as the floor truth for training and validation from the detection method.

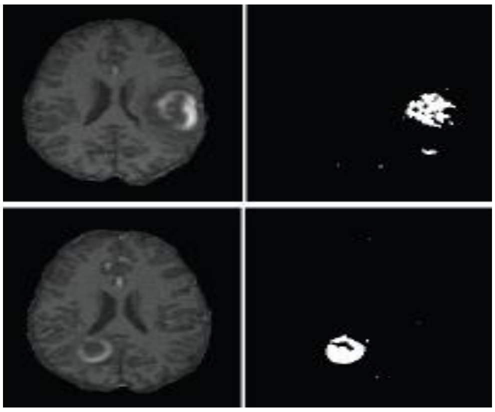

Fig.3 left: original image, right: segmented image

The images were pre-processed as aforementioned and the four forms of features were extracted from the images to be properly used as the training data set for the classification. A leave-one-out validation was performed on the images.
The workflow of this technique is shown within the next figure. Each MRI in the training set is first pre-processed to minimize the intensity bias and to remove the non-brain tissue. The pre-processing also incorporates multi-modality within-subject registration and co-registration to a typical template for cross subject comparison.
Next, four kinds of features (i.e., intensity, symmetry, shape deformation, and texture features) are extracted from the pre-processed images. Feature selection and fusion are carried out using AdaBoost. For new subjects, the selected features computed in the training process will probably be extracted and tumor will probably be detected when using the trained classifier.

D. Brain Tumor Detection and Segmentation Using Histogram Thresholding

The idea is reliant mainly on three points: (i) the symmetrical structure on your brain, (ii) pixel intensity of image and (ii) binary image conversion. It is a well liked undeniable fact that human brain is symmetrical about its central axis and throughout this work this has been assumed that the tumor is either to the left or to even the proper side on the brain. MR image of the human brain is frequently broken into sub region in order that white matter, gray matter, blood cells and cerebrospinal fluid can simply be detected. Tumor is totally nothing nevertheless the collection of blood cells at some specific point/s. The image of a brain in MRI is represented through pixel intensity. In gray colour images the intensity lies between 0-255 with 0 indicating for black and 255 is assigned with the white colour. The blood cells (RED colour in RGB) are represented by white colour and 255 pixel intensity. Most of the gray matter is pixel intensity fewer than 255.
Region of images is the entire quantity of the pixels within neighbourhood which is often calculated within the length units by multiplying just how many pixels using the dimension of one pixel. To calculate just how many pixels within the cropped image the big event Bwarea () is used. This function calculates the cell number pixels within the image. The very best click the image and going directly on through the detail property gives another detail of the image:
Size of image, e.g., 600X400

- Horizontal resolution, e.g., 96 dpi.
- Vertical resolution, e.g., 96 dpi

From horizontal and vertical resolution one will discover the dimension of someone pixel. The algorithm used is follows: One may find 96 pixels in an inch. Hence vertical dimension of any pixel is 1/96 inch. Similarly horizontal dimension of someone pixel is 1/96 inch. Region of single pixel is equal to (1/96)*(1/96) square inch.
A = (1/96)*(1/96)
Part of the tumor = A*total

IV. LITERATURE SURVEY

Abdel-Maksoud et al. (2015) [1] presented an efficient image segmentation approach using K-means clustering technique integrated with Fuzzy C-means algorithm. It has been followed closely by thresholding and level set segmentation stages to provide accurate brain tumor detection. The proposed technique could possibly get advantages of the K-means clustering for image segmentation in the aspects of minimal computation time. Additionally, it could possibly get advantages of the Fuzzy C-means in the aspects of accuracy. The performance of the proposed image segmentation approach was evaluated by comparing it with some state of the art segmentation algorithms in the event of accuracy, processing time, and performance. The accuracy has been evaluated by comparing the outcomes with the floor truth of each processed image. The experimental results clarified the potency of proposed approach to manage an increased number of segmentation problems via improving the segmentation quality and accuracy in minimal execution time.**Halder et al. (2014) [2]** has proposed a method of brain tumor detection , which can locate brain tumor in the brain MRI images. This technique extracts the tumor by utilizing K-means algorithm accompanied by Object labelling algorithm. Also, some pre-processing steps i.e. median filtering and morphological operation are useful for tumor detection purpose. It is observed that the experimental link between the proposed method gives better result in comparison to other techniques.**Preetha and Suresh (2014) [3]** has discussed that the Image Segmentation is vital and challenging to visualize the tissue of human for analyzing the MR images. In brain MR images, the boundary of tumor tissue is highly irregular. Deformable models and Region based methods are extensively useful for medical image segmentation, to locate the boundary of the tumor. Problems connected with non-linear distribution of real data, User interaction and poor convergence to the boundary region limited their usefulness. Clustering of brain tumor images, using Fuzzy C means is robust and effective for tumor localization. Even although the proposed method has high computational complexity, it shows superior results in segmentation efficiency and convergence rate. The Fuzzy C means clustering with the extension of Feature extraction and classification is extremely promising in the field of brain tumor detection.**Zeljkovic et al. (2014) [4]** has shown that the MRI or CT scan images are primary follow up diagnostic tools whenever a neurologic exam indicates possible of a main or metastatic brain tumor existence. The tumor tissue mainly appears in brighter colours compared to the rest of the regions in the brain. Based with this observation, an automated algorithm for brain tumor detection and medical doctors ‘assistance in facilitated and accelerated diagnosis procedure has been developed and initially tested on images obtained from the patients with diagnosed tumors and healthy subjects..**Dvorak et al. (2013) [5]** has deal with automatic brain tumor detection in magnetic resonance images. The goal is to determine whether the MR images of a brain include a tumor or not. The proposed method works together with T2-weighted magnetic resonance images, where the top is vertically aligned. The detection is founded on checking the left-right symmetry of mental performance that will be the assumption for healthy brain. The algorithm was tested by fivefold cross-validation technique on 72 images of brain containing tumors and 131 images of healthy brain. The proposed method reaches the real positive rate of 91.16% and the real negative rate of 94.68%.**Salah et al. (2013) [6]** has presented an algorithm for fully automated brain tumor segmentation from only two magnetic resonance image modalities. The technique is founded on three steps: (1) alternating different quantities of automatic histogram-based multi-thresholding step, (2) performing a fruitful and fully automated process of skull-stripping by evolving deformable contours, and (3) segmenting both Gross Tumor Volume and edema. The technique is tested using 19 hand-segmented real tumors which show very accurate results compared to a really recent method (STS) with regards to the Dice coefficient. Improvements of 5% and 20% respectively for segmentation of edema and Gross Tumor Volume have now been recorded.**Ulku et al. (2013) [7]** has discussed that the Computer-aided detection (CAD) systems help to radiology experts in mass detection using image processing techniques. This study aims to appreciate mass detection process on brain MRI (Magnetic Resonance Imaging) images. The CAD system has been presented which is founded on histogram equalization and morphological image processing techniques. The processes are carried out through 125 MR images which are taken from 11 people which are 8 people who have tumors, 3 people without tumors. In classification stage which can be the past stage of the computer-aided detection systems, 6 classification algorithms are tested in the Rapid Miner program and these algorithms are compared together to exhibit CAD system accuracy. **Vijay and Subhashini (2013) [8]** has discussed that the Segmentation of images holds an important position in the region of image processing. It becomes more important while typically working with medical images where pre-surgery and post surgery decisions are needed for the objective of initiating and speeding up the recovery process. Computer aided detection of abnormal growth of tissues is primarily motivated by the necessity of achieving maximum possible accuracy. Manual segmentation of those abnormal tissues can't be in contrast to modern day's high speed computing machines which enable us to visually observe the quantity and location of unwanted tissues. **Abdullah et al. (2012) [9]** has proposed a brain tumor detection method predicated on cellular neural networks (CNNs). Brain tumor is definitely an abnormal growth of cells inside the skull. To examine the positioning of tumor in mental performance, Magnetic Resonance Imaging (MRI) is used. Radiologists will evaluate the grey scale MRI images. This procedure is actually time and energy consuming. To overcome this dilemma, an automated detection method for brain tumor using CNN is developed. **Bhattacharjee and Chakraborty (2012) [10]** explained that algorithm is developed to trait out tumor from unhealthy brain Magnetic Resonance (MR) imagery. This is dependent on quality factor contrast of two filters; adaptive median filter is chosen for de-noising the imagery. Picture slicing and recognition of important planes are completed. Logical operations are useful on chosen slices to acquire the processed picture viewing the tumor section. This algorithm is based on the application of Principal Components Analysis (PCA). This algorithm pays to on unique rare imagery along with on the processed images. It verifies the average person efficiency of the developed picture processing algorithm to identify brain tumor. **Ghanavati et al. (2012) [11]** presented a multi-modality framework for automatic tumor detection is presented, fusing different Magnetic Resonance Imaging modalities including T1-weighted, T2-weighted, and T1 with gadolinium contrast agent. The symmetry, texture features, intensity and shape deformation were extracted from each image. The AdaBoost classifier was used to choose the most discriminative features and to segment the tumor region. Multi-modal MR images with tumor have been used as the floor truth for training and validation of the detection method. Preliminary results on simulated and patient MRI show 100% successful tumor detection with average accuracy of 90.11%.**Maiti and Chakraborty (2012) [12]** has proposed a new method for brain tumor detection. For this specific purpose watershed method is employed in combination with edge detection operation. It is a shade based brain tumor detection algorithm using colour brain MRI images in HSV colour space. The RGB image is transformed into HSV colour image by that your image is separated in three regions saturation, intensity, and hue. After contrast enhancement watershed algorithm is placed on the image for every single region. On the output image, Canny edge detector is placed. After combining the three images, final brain tumor segmented image is obtained. The algorithm has been applied on twenty brain MRI images. The developed algorithm has given promising results. **Natarajan et al. (2012) [13]** has studied that the Medical Image Processing is a sophisticated and challenging field nowadays. Processing of MRI images is among the parts with this field. This paper proposes a technique for efficient detection of a brain tumor in MRI brain images. The methodology contains the next steps: pre-processing by using sharpening and median filters, enhancement of image is performed by histogram equalization; segmentation of the image is performed by thresholding. This method is then followed by the further application of morphological operations. Finally the tumor region can be obtained utilizing the technique of image subtraction.**Parisot et al. (2012) [14]** explained that new technique for detection, segmentation and characterization of brain tumor. This process exploits previous information in the structure of an extra graph on behalf of the predictable spatial positions of tumor classes. Such information is as well as picture based categorization techniques alongside spatial smoothness constraints towards producing a regular recognition map inside a united graphical model formulation. Towards most favourable use of prior information, a two layer organized graph is measured with one layer equal to the low-grade glioma type (description) and another layer to voxel-based decisions of tumor occurrence. Proficient linear programming together in conditions of performance in addition to in terms of computational load is considered to recuperate the cheapest potential of the objective purpose. **Raza et al. (2012) [15]** has proposed a denoising algorithm which eliminates salt and pepper noise from digital images which are highly corrupted by salt and pepper noise. Several methods have already been introduced to eliminate fixed value impulse noise (salt and pepper noise) from digital images such as for instance median filter (MF), adaptive median filter (AMF), Decision based algorithms (DBA) etc. Several algorithms fail while removing the noise at high density and do not preserve fine details of the image. The proposed algorithm (PA) shows better results than existing filtering methods. The algorithm tested and compared for Peak Signal-to-Noise Ratio (PSNR) and Image Enhancement Factor (IEF) with various existing methods.**Subashini et al. (2012) [16]** has discussed that mental performance tumor detection is a significant application in recent days. The medical problems are severe if tumor is identified at the later stage. Hence diagnosis is important at the earliest. MRI is the existing technology which enables the detection, diagnosis and evaluation. In this work, the images obtained through MRI are segmented and then fed to a model referred to as Pulse coupled neural network for detecting the presence of tumor in mental performance image. The physician could seek the aid of this model if the input MRI brain images are far more in number and the network would help the physician to save lots of time for further analysis. The task also utilizes back propagation network for classification. The networks are less complex in nature and hence the processing of MRI brain images is very simple. The network classifies the input images as normal and tumor containing. The tumor might be benign and malignant and it takes medical support for further classification.

V. COMPARISON TABLE

Table 1 shows the comparison among various techniques.

TABLE 1: COMPARISON AMONG VARIOUS TECHNIQUES

References	Authors	Year	Technique	Features	Limitations
[1]	Abdel-Maksoud, Eman, Mohammed Elmogy, and Rashid Al-Awadi	2015	watershed algorithm, Hough transform ,automatic nuclei localization mechanism	Quality work	Performs poor on 3D object segmentation
[2]	Halder, Amitava, Chandan Giri, and Amiya Halder	2014	K-means algorithm	median filtering and morphological operation	has ignored the poor quality images
[3]	Preetha, R., and G. R. Suresh	2014	Fuzzy C means	high computational complexity, it shows superior results in segmentation efficiency and convergence rate	neglected the use of fuzzy and region growing segmentation
[4]	Zeljkovic, V., C. Druzgalski, Y. Zhang, Z. Zhu, Z. Xu, D. Zhang, and P. Mayorga	2014	semiautomatic brain tumor segmentation algorithm	encourage the development and evaluation of segmentation	poor in case of time complexity.
[5]	Dvorak, Pavel, Walter Kropatsch, and Karel Bartusek Sapiro	2013	minimization and geometric active contours	uniqueness, stability, and correctness	Performs poor on 3D object segmentation
[6]	, Mohamed Ben, Idanis Diaz, Russell Greiner, Pierre Boulanger	2013	real-time cooperative multitarget tracking system	Effectiveness	has ignored the poor quality images
[7]	Ulku, Eyup Emre, and Ali Yilmaz Camurcu	2013	weighted Gaussian filtering , object segmentation	preserves true object borders	neglected the use of fuzzy and region growing segmentation

[8]	Vijay, J., and J. Subhashini	2013	Atlas-based segmentation	good registration	Poor in case of time complexity.
[9]	Abdullah, Azian Azamimi, Bu Sze Chize, and Yoshifumi Nishio	2012	2D-to-3D conversion	performance is satisfactory for images and short video clips	Performs poor on 3D object segmentation
[10]	Bhattacharjee, Rupsa, and MonishaChakraborty	2012	1) Brain tumor detection based on multi-parameter	Quality work	has ignored the poor quality images
[11]	Ghanavati, Sahar, Junning Li, Ting Liu, Paul S. Babyn, Wendy Doda,	2012	Brain Tumors Extraction		neglected the use of fuzzy and region growing segmentation
[12]	Maiti, I., and M. Chakraborty	2012	semi-automatic segmentation technique	Effective	poor in case of time complexity.
[13]	Parisot, Sarah, HuguesDuffau, StéphaneChemouny, and Nikos Paragios	2012	modified region growing technique	Efficient sensitivity, specificity and accuracy values	Performs poor on 3D object segmentation
[14]	Raza, Md Tabish, and Suraj Sawant	2012	Hybrid clustering technique	quality and accuracy in minimal execution time	has ignored the poor quality images

VI. CONCLUSION AND FUTURE SCOPE

The brain tumor detection is a critical application of medical image processing. The literature survey indicates that the most of the methods which are existing has ignored the images which are of poor quality like images with high noise or low brightness. Also the lot of the existing work with tumor detection has neglected the utilization of object based segmentation. The overall goal of this research work would be to propose an efficient brain tumor detection using the feature detection and roundness metric. To boost the tumour detection rate further we have integrated the proposed hybridization of fuzzy and region growing segmentation based tumour detection with the trilateral filter. The proposed technique has the capability to produce effective results even in case of high density of the noise.

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