

Brain Tumor Segmentation Using K-Means and Adaptive K-Means Hybrid Clustering Technique

Santhosh Kumar R¹, Dr Naveena C²

^{1,2}Department of Computer Science and Engineering S J B Institute of Technology, Bengaluru, Karnataka, India

Abstract: Irregular growth of cancer causing cells within brain stated as brain tumor. In medical and image processing field, segmentation and classification of brain tumor in MRI images is very challenging task. Survey and researches proves that number of brain tumor patients died in past few years because of inaccurate detection and location of tumor, hence proper segmentation of brain MRI images is very necessary. Classifying the normal cells and abnormal cells after segmentation helps in proper treatment. In this thesis, an effort towards development and analysis of some contemporary brain tumor segmentation and classification techniques are proposed. Proposed work can be categorized into two phases; firstly segmentation techniques such as histogram thresholding and adaptive k-means clustering techniques are explored; secondly, support vector machine and principal component analysis will be analyzed as classification techniques.

Keywords: Brain Tumor; Medical image segmentation; K-means clustering; Expectation Maximization; Adaptive K-means clustering.

I. INTRODUCTION

A brain tumor is an intracranial solid neoplasm which is defined as an abnormal growth of cells within the brain or the central spinal canal. Brain tumors can be malignant (cancerous) or benign (non-cancerous). Low class gliomas and meningiomas are gentle cysts, and glioblastoma multiforme is a destructive swelling whichever represents divine universal elementary with cyst. Benign Intellectual lumps have an equal edifice whatever did not incorporate tumor cells and they may be each of two transmission reasonably monitored or totally aloof surgically and they do not remain over. The network of lethal with carcinomas is opposed and it stops malignancy cells and that perhaps treated with radiotelephone therapy, eradicator or a partnership of both, and they are lethal. Therefore, diagnosing the Einstein Cysts in an embezzle time is very constitutional for then treatments. Neurology and key neuroscience have been significantly state-of-the-art by utilizing estimate tools that permit in vivo monitoring of the intellect. The ultimate goal of brain tumor imaging analysis is to extract they patient-specific important clinical information, and their diagnostic features. Brain tumor segmentation consists of separating the different tumor tissues (solid or active tumor, edema, and necrosis) from normal brain tissues: gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF).

II. RELATED WORK

Medical image segmentation is considered as a hot research topic. Several researchers have suggested various methodologies and algorithms for image segmentation. For example, Bandhyopadhyay and Paul [1] proposed a brain tumor segmentation method based on K-means clustering technique. The method consists of three steps: K-means algorithm based segmentation, local standard deviation guided grid based coarse grain localization, and local standard deviation guided grid based fine grain localization. The extraction of the brain tumor region from the processed image requires the segmentation of the brain MRI images to two segments. One segment contains the normal brain cells consisting of Grey Matter (GM), White Matter (WM), and the Cerebral Spinal Fluid (CSF).

Meena and Raja [2] proposed an approach of Spatial Fuzzy C-means (PET-SFCM) clustering algorithm on Positron Emission Tomography (PET) scan image datasets. The algorithm is joining the spatial neighborhood information with classical K-means and updating the Objective function of each cluster. Spatial relationship of neighboring pixel is an aid of image segmentation. These Neighboring pixels are highly renovated the same feature data. In spatial domain, the memberships of the neighbor centered are specified to obtain the cluster distribution statistics. They calculated the weighting function based on these statistics and applied into the membership function. Their algorithm is tested on data collection of patients with brain disease.

Glavan and Holban [3] proposed system that using a convolution neural network (CNN) as pixel classifier for the segmentation process of some X-ray images. The organization analyzes each element from the figure and tries to analyze them in to two classes bone and nonbone. Their CNN obtained admirable favor diverge to alternative configurations. For ensuring a margin coaching time

of the structure, they used only the gain areas from an icon. Their method perceived the vital bone areas, but the problems came when the bone area granted irregularities and take more implementation materialize discipline

Tatiraju and Mehta [4] introduced image segmentation using K-means clustering, Expectation Maximization (EM), and Normalized Cuts (NC). They analyzed the two former unsupervised learning algorithms and compared them with a graph-based algorithm, the Normalized Cut algorithm. They applied the partitioning algorithm to gray-scaled images with varying value of k (number of clusters). For smaller values of k , the K-means and EM algorithms give good results. For larger values of k , the segmentation is very coarse; many clusters appear in the images at discrete places.

Yerpude and Dubey [5] proposed color image segmentation using K-Medoids Clustering. The idea of the algorithm is to find clusters of objects by finding the Medoids for each cluster. Each remaining object is clustered with the Medoid or representative objects to which it is the most similar. K-Medoids method uses representative objects as reference points rather than taking the mean value of the objects in each cluster. The algorithm takes the input parameter k and the number of clusters to be partitioned among a set of n objects. The segmented images are highly dependent on the number of segments or centers. They did not consider finding optimal number of segments to provide more accurate results.

[6], Explains segmentation of brain tumor by k-means & fuzzy c-means clustering. Adaptive K-means gives more accurate results as compared to that of clustering carried out by k-means. Using adaptive K-means algorithm can detect type (stage) of tumor whether it is primary or secondary tumor, intern helps in the diagnosis process. This paper uses the method that includes preprocessing (RGB to gray conversion & filtering the input image to remove high frequency components and noise), segmentation using adaptive K-means and k-means clustering and finally features are extraction. Noise removed from the input image in the preprocessing step by using the median filter.

III. PROPOSED WORK

Brain tumor segmentation in MR images has been recent area of research in the field of automated medical diagnosis as the death rate is higher among humans due to brain tumor Magnetic fullness (MR) figures are a very profitable tool to disclose the lump prosperity in intellect but particular wit perception disjunction is a grim and dull operation. The movement of with swelling regulation in with divine challenging tasks as is a harsh (same sign forever as that of with balance) to hypo fierce (darker than the wit balance) worth of intellect Cancers, assortment creates dubiety in lump distribution. Accurate disjunction of head Cancers is an serious task for special medicinal letters.

A. De-Noising

MRI images are regularly perverted by disturbances like Gaussian and Poisson noise [20]. The vast estate of the de-noise breakthrough adopt extra clear Gaussian noise. The number of algorithms that implemented for Gaussian noise elimination, such as edge preserving bilateral filter, total variation, and non-local means. In this paper, we used median filter [16,18]. Median filtering is a nonlinear filter that is used as an effective method for removing noise while preserving edges. It works by moving pixel by pixel through the image, replacing each value with the median value of neighboring pixels. Image processing researchers commonly assert that median filtering is better than linear filtering for removing noise in the presence of edges [17]. The output of this sub-step in preprocessing is the free noising MRI image.

B. Skull Removal

Image background does not normally incorporate any profitable info but develop the processing time. Therefore, removing background skull, scalp, eyes, and all structures that are not in the interest decrease the amount of the memory used and increased the processing speed. Skull removed is done by using BSE (brain surface extractor) algorithm. The BSE conclusion is used only with MRI drawings. It filters the figure to clear away irregularities, detects penetrate the icon, and performs semantic erosions and wit segregation. It also performs face surplus and impression masking. The production about sub step is the free circulate MRI image.

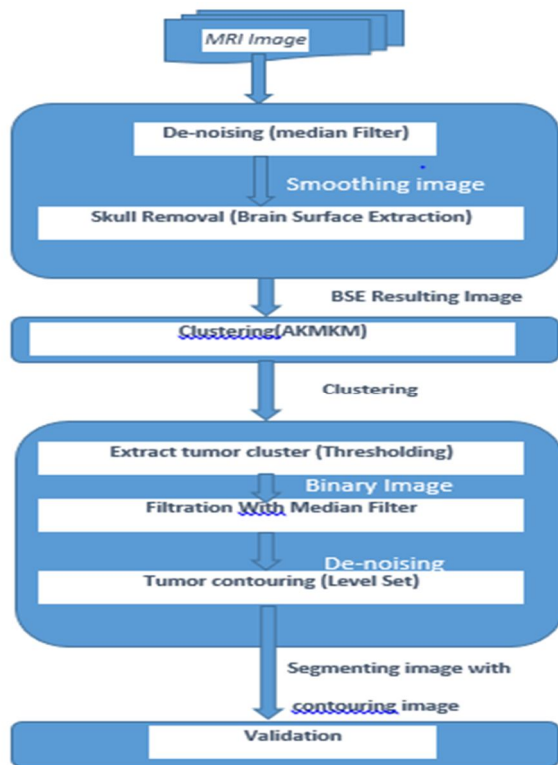


Figure (1): The framework of the proposed image segmentation system.

C. Clustering Stage

By de-noising the MRI image and removing skulls, the images are fed to AKMKM technique by initializing cluster numbers k , max iterations, and termination parameter. In k-means we need to enter the k value where as in adaptive k-means it takes automatically. The cluster centers are calculated by:

$$MU = \frac{(1:k) * \pi}{(k+1)} \quad (1)$$

where MU is the initial means that can be calculated due to k . k is the number of clusters and π is defined as:

$$\pi = \max(\text{MRI image}) + 1 \quad (2)$$

Then, assign each point to the closest cluster center based on a low distance by checking the distance between the point and the cluster centers then re-compute the new cluster centers. It repeats until some convergence criterion is met.

D. Extraction and Contouring Stage

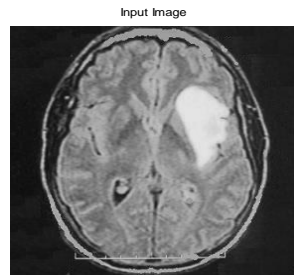
In this stage, we used two segmentation methods: thresholding and active contour level set methods:

- 1) *Thresholding Segmentation*: It is intensity-based segmentation. Thresholding or image binarization are the serious techniques in image processing and computer vision. The image, that is obtained by thresholding, has the advantages of lesser stockpile location, fast processing speed, and ease of direction, equal gray achievement image and that normally contains a piles of gray achievements (maximum 256 levels) [18]. The harvest about step is the slash impression with dark history and brightness lump area.
- 2) *Active Contour by Level Set*: Active contours have been used for image segmentation and boundary tracking. The idea behind this isto represent the boundary shapes in the form of closed curves. i.e. contours, and iteratively modify them by applying shrink/ expansion operations according to the constraints. An advantage of the active contours as an image segmentation method is that they partition an image into sub-regions with continuous boundaries. While the edge detectors based on the threshold or local filtering, it often results in discontinuous boundaries. The use of level set theory has provided more flexibility and convenience in the implementation of active contours.

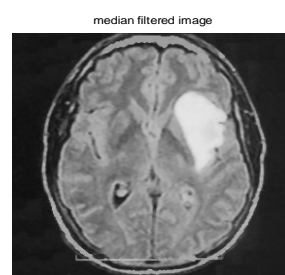
E. Validation Stage

In validation stage, the segmented images by AKMKM were compared to the ground truth in cases of the third data set as illustrated in experimental results. the number of pixels that belong to a cluster and is segmented into that cluster. Recall, or sensitivity is defined as the number of the true positives divided by the total number of elements that belong to the positive cluster [11–13].

IV. IMPLEMENTATION



Fig(2a)

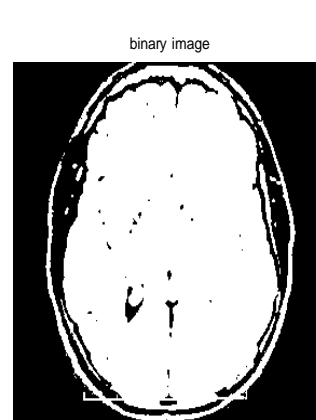


Fig(2b)

Input images to the system are MRI Image as shown in Fig(2a), These images are corrupted by disturbance. In order to remove noise in the MRI image we use median filter while preserving edges. Median filtering is very widely used in image processing because, under certain conditions, it preserves edges while removing noise as shown in Fig(2b). Median filtering is one kind of smoothing technique, as is linear Gaussian filtering. All smoothing techniques are effective at removing noise in smooth patches or smooth regions of a signal, but adversely affect edges. Often though, at the same time as reducing the noise in a signal, it is important to preserve the edges. Edges are of critical importance to the visual appearance of images, for example.



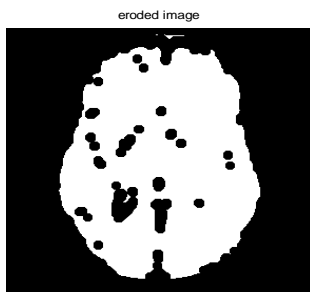
Fig(3a)



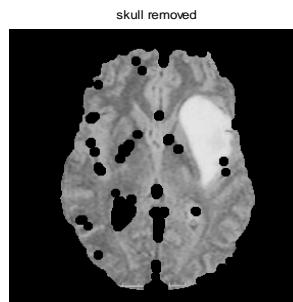
Fig(3b)

Fig(2a) depicts Edge detection, it is an image processing technique for finding the boundaries of objects within images. It works by detecting discontinuities in brightness. Edge detection is used for image segmentation and data extraction in areas such as image processing, computer vision, and machine vision. Common edge detection algorithms include Sobel, Canny, Prewitt, Roberts, and fuzzy logic methods. $BW = \text{edge}(I)$ takes a grayscale or a binary image Fig(3b) I as its input, and returns a binary image BW of the same size as I , with 1's where the function finds edges in I and 0's elsewhere.

$BW = \text{im2bw}(I, \text{level})$ converts the grayscale image I to a binary image. Specify level in the range $[0,1]$. This range is relative to the signal levels possible for the image's class. Therefore, a level value of 0.5 is midway between black and white, regardless of class. To compute the level argument, you can use the function graythresh.



Fig(4a)



Fig(4b)

Fig(4a) shows that Erosion image (usually represented by \ominus), it is one of two fundamental operations (the other being dilation) in morphological image processing from which all other morphological operations are based. It was originally defined for binary images, later being extended to grayscale images, and subsequently to complete lattices. The basic idea in binary morphology is to probe an image with a simple, pre-defined shape, drawing conclusions on how this shape fits or misses the shapes in the image. This simple "probe" is called structuring element, and is itself a binary image.

Image background does not usually contain any useful information but increase the processing time. Therefore, removing background, skull, scalp, eyes, and all structures that are not in the interest decrease the amount of the memory used and increased the processing speed. Skull removed is done by using BSE (brain surface extractor) algorithm as shown in Fig(4b). The BSE algorithm is used only with MRI images. It filters the image to remove irregularities, detects edges in the image, and performs morphological erosions and brain isolation. It also performs surface cleanup and image masking. The output of this sub step is the free noising MRI image contains only the human brain.



Fig(5a)

Finally the image Fig(5a) obtained from the proposed system can detect the tumor in the input MRI image.

V. CONCLUSION

Image segmentation plays a significant role in medical image. In the field of medical diagnosis, an extensive diversity of imaging techniques is available presently, such as CT and MRI. MRI is the most effectively image model used for diagnostic image examination for brain tumor. The MRI scan is more comfortable than CT scan for diagnosis. Our framework consists of four stages: pre-processing (de-noising and skull removal), clustering (hybrid approach), extraction and contouring (thresholding and level set), and validation stages. From the experimental results, we proved the effectiveness of our approach in brain tumor segmentation. In future work, the 3D evaluation of the brain tumor detection using 3D slicer will be carried out. As well as to increase the efficiency of the segmentation process, an intensity adjustment process will provide more challenging and may allow us to refine our segmentation techniques to the MRI brain tumor segmentation

REFERENCES

- [1] Bandhyopadhyay SK, Paul TU. "Automatic Segmentation of Brain Tumour from Multiple Images of Brain MRI" International Journal ApplInnovatEng Manage (IJAIEM) PP:240–8 Vol:2(1) 2013.
- [2] Meena A, Raja K. "Spatial Fuzzy C-means PET Image Segmentation of Neurodegenerative Disorder Spatial Fuzzy C-means PET Image Segmentation of Neurodegenerative Disorder" Indian Journal ComputSciEng (IJCSSE) PP:50–5 Vol:4(1) 2013
- [3] Glavan CC, Holban S. "Segmentation of Bone Structure in X-ray Images Using Convolutional Neural Network" AdvElectrComputEng PP:1–8 Vol:13(1) 2013
- [4] Tatiraju S, Mehta A. "Image Segmentation using k-means Clustering, EM and Normalized Cuts" University Of California Irvine, technical report.



- [5] Yerpude A, Dubey S. "Colour Image Segmentation using K-medoids Clustering" International Journal ComputTechnolAppl PP:152-4 Vol:3(1) 2012.
- [6] Alan Jose1, Sambath, M., & Ravi, S., Brain Tumor Segmentation Using K-Means Clustering And Fuzzy C-Means Algorithms And Its Area Calculation, International Journal of Innovative Research in Computer and Communication Engineering, Vol. 2, Issue 3, March 2014.
- [7] Moumen T El-Melegy and Hashim M Mokhtar, Tumor segmentation in brain MRI using a fuzzy approach with class center priors, El-Melegy and Mokhtar EURASIP Journal on Image and Video Processing, volume 21, 2014.
- [8] Upasana Gaikwad, KanikaDebbarma&SilkshaThigale, Survey Paper on Clustering based Segmentation Approach to Detect Brain Tumor from MRI Scan,International Journal of Computer Applications (0975 – 8887), Volume 115, no. 14, April 2015
- [9] Swathi, P. S., Deepa Devassy, Vince Paul, &Sankaranarayanan, P.N., Brain Tumor Detection and Classification Using Histogram Thresholding and ANN, International Journal of Computer Science and Information Technologies,Vol. 6, no. 1, 2015, pp. 173-176.
- [10] Manoj K Kowar, and Sourabh Yadav, Brain Tumor Detction and Segmentation Using Histogram Thresholding, International Journal of Engineering and Advanced Technology (IJEAT) ISSN: 2249 – 8958, Volume-1, Issue-4, April 2012.
- [11] CH. Rambabu, & B. Siva Ayyappa Kumar, Brain Tumor Classification Using Multi Wavelet Transform and Neural Network, International Journal of Advanced Research in Computer Science and Software Engineering, Volume 4, Issue 9, September 2014.
- [12] Yash Sharma, &Megha Chhabra. (2015).An Improved Automatic Brain Tumor Detection System, International Journal of Advanced Research in Computer Science and Software Engineering, (Volume 5, Issue 4).
- [13] Nelly Gordillo Castillo, Pilar Sobrevilla, & Eduard Montseny, A New Fuzzy Approach to Brain Tumor Segmentation, CONFERENCE PAPER in IEEE international conference on fuzzy systems, JULY 2010.
- [14] Jin Liu, Min Li, Jianxin Wang, Fangxiang Wu, Tianming Liu, and Yi Pan, A Survey of MRI-Based Brain Tumor Segmentation Methods, Volume 19, Number 6, December 2014, pp578-59
- [15] CH. Rambabu, & B. Siva Ayyappa Kumar, Brain Tumor Classification Using Multi Wavelet Transform and Neural Network, International Journal of Advanced Research in Computer Science and Software Engineering, Volume 4, Issue 9, September 2014.
- [16] Madheswaran, M., and AntoSahayaDhas, D., Classification of brain MRI images using support vector machine with various Kernels, Biomedical Research, vol. 26, no. 3,2015 pp. 505-513.
- [17] EashaNoureen, & Dr. Md. Kamrul Hassan, Brain Tumor Detection Using Histogram Thresholding to Get the Threshold point, IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE). Volume 9, Issue 5 Ver. III (Sep – Oct. 2014), PP 14-19
- [18] Amrutha Ravi, Sreejith S.,A Review on Brain Tumour Detection Using Image Segmentation, International Journal of Emerging Technology and Advanced Engineering. Volume 5, Issue 6, June 2015
- [19] Nelly Gordillo Castillo, Pilar Sobrevilla, & Eduard Montseny, A New Fuzzy Approach to Brain Tumor Segmentation, CONFERENCE PAPER in IEEE international conference on fuzzy systems, JULY 2010
- [20] M. Selvi& K. Maheswari, A Review on Brain Tumour Segmentation, International Journal of Advanced Research in Computer and Communication Engineering, Vol. 4, Issue 10, October 2015.