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A REVIEW OF DIFFERENT SEGMENTATION TECHNIQUES USED IN BRAIN TUMOR DETECTION

Authors:
NICER NAVID K R[1] and Dr. K C JAMES[2]
[1]Student, Mtech-Engineering Statistics, Department of Statistics,
Cochin University of Science and Technology (CUSAT)
Kochi-682 022, KERALA, INDIA.
[2]Professor, Department of Statistics,
Cochin University of Science and Technology (CUSAT)
Kochi-682 022, KERALA, INDIA.
[1]e-mail: -**nicer.navid@gmail.com**
[2]e-mail: - **jamesmech@cusat.ac.in**

ABSTRACT

A tumor is a solid lesion formed by an abnormal growth of cells which looks like a swelling.Each year more than 200,000 people in the United States are diagnosed with a primary or metastatic brain tumor.The use of advanced computer technology is now extensevily used in fields such as cancer research. MRI is a currently popular for the study of tumor in body tissues. MRI is a magnetic field which builds up a picture and has no known side effects related to radiation exposure.In MR images, the amount of data is high for manual interpretation and analysis.Segmentation is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyse.The segmentation of brain tumor from images is composed of several steps. Manual segmentation of brain MR images is a very difficult and time consuming task. Numerous segmentation techniques have been proposed for the detecting and isolating the tumour by various authors. In this paper we perform a comparative analysis of the segmentation techniques currently available for tumor detection. This paper investigates the performance of the existing segmentation techniques that are currently used using different performance parameters.

Key Words:Image segmentatation,tumordetection,k-means segmentation,edge detection

I. INTRODUCTION

Brain tumors are abnormal proliferations of cells in brain. An early detection of the tumor ie its position and properties can greatly improve the chances of survival.The use of computer technology in medical decision support is now widespread across a wide range of medical area such as cancer research[1].MRI is a viable option now for the study of tumor in soft tissues. MRI is a magnetic field which builds up a picture and has no known side effects related to radiation exposurefiles for formatting[2].In MR images, the amount of data is high for manual interpretation and analysis.Image features represent the distinctive characteristics of an image that needs to be segmented.MRI technique relies on the properties of magnetically-excited hydrogen nuclei of water molecules in the body[2].The patient under study is briefly exposed to a burst of radio-frequency energy, which, in the presence of a magnetic field, puts the nuclei in an elevated energy state. As the molecules undergo their normal, microscopic tumbling, they shed this energy into their surroundings, in a process referred to as relaxation. Images are created from the difference in relaxation rates in different tissues.

Brain MR images have a number of features, especially the following: First, they are statistically simple: MR Images are theoretically piecewise constant with a small number of classes. Second, they can have relatively high contrast between different tissues[3].Unlike many other medical imagingmodalities, the contrast in an MR image depends strongly upon the way the image is acquired. By altering radio-frequency(RF) and gradient pulses, and by carefully choosing relaxation timings, it is possible to highlight different components in the object being imaged and produce high-contrast images. These two features facilitate segmentation.

Image segmentation is a process of pixel classification. An image is segmented into subsets by assigning individual pixels to classes. It is an important step towards pattern detection and recognition. Segmentation is one of the first steps in image analysis[4].It refers to the process of partitioning aimage into multiple regions

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Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. The level ofsegmentation is decided by the particular characteristics of the problem being considered.

Image segmentation is an old research topic, which started around 1970, but there is still no robust solution toward it. There are two main reasons; the first is that the content variety of images is too large, and the second one is that there is no benchmark standard to judge the performance. Image segmentation is identification of homogeneous regions in the image[5]. Many algorithms have been elaborated for gray scale images. In this paper we review different image segmentation techniques along with their advantages and disadvantages

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II. SEGMENTATION TECHNIQUES

There are many Automatic image segmentation techniques.The commonly used ones are the following :- ,(1) Clustering Methods, (2) Thresholding Methods, (3) Edge-Detection Methods, (4) Region-Based Methods and (5) watershed segmentation[6].

II.1 Clustering Methods :Clustering is a process whereby a data set (pixels) is replaced by cluster[7]; pixels may belong together because of the same color, texture etc. Two important clustering methods are discussed below. The difficulty in using either of the methods directly is that there are lots of pixels in an image.

II.1.1 K means clustering An approach is to write down an objective function and then build an algorithm. The K-means algorithm is an iterative technique that is used to partition an image into K clusters, where each pixel in the image is assigned to the cluster that minimizes the variance between the pixel and the cluster center and is based on pixel color, intensity, texture, and location, or a weighted combination of these factors. This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K [8].

Steps of the K-Means clustering algorithm[8]**:**

1. Initialization – define the number of clusters and randomly select the position of the centers for each cluster or directly generate k seed points as cluster centers.
2. Assign each data point to the nearest cluster center.
3. Calculate the new cluster centers for clusters receiving new data points and for clusters losing data points.
4. Repeat the steps 2 and 3 until a convergence criterion is met (when there is no exchange of data points between the k clusters). The aim of the K-Means is the minimization of an objective Function:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2$$

Where

$\left\| x_i^{(j)} - c_j \right\|^2$ is the distance measure (usually Euclidian metric) between adata point $x_i^{(j)}$ and the cluster center cj (this is an indicator of the distance of the n data points from the cluster centers). There are situations when the K-Means algorithm doesn’t find the optimal solution corresponding to the global objective function J and in addition is sensitive to the initialization process that selects the initial cluster centers that are usually randomly picked from input data. The main advantages of this algorithm are its simplicity and low computational cost, which allows it to run efficiently on large datasets. The main drawback is the fact that it does not systematically yield the same result each time the algorithm is executed and the resulting clusters depend on the initial assignments. The K-Means algorithm maximizes inter-cluster (or minimizes intra-cluster) variance, but does not ensure that the algorithm will not converge to local minima due to an improper starting condition (initialization of the cluster centers).

K- means is a widely used clustering algorithm to partition data into k clusters.Clusteing this the process for grouping data points with similar feature vectors into a single cluster and for grouping data points with dissimilar feature vectors into different clusters.[9] Let the feature vectors derived from l clustered data be X-{Xi/i=1,2-----l}. The generalized algorithm initiates k cluster centroids C={Cj/j=1,2,--------k} by randomly selecting k feature vectors from X. Later the feature vectors are grouped aregrouped into k clusters using a selected distance measure such Euclidean distance so that d=mod(Xi-Cj).

II.1.1.1 **Deciding the number of clusters**

The number of clusters should match the data. An incorrect choice of the number of clusters will invalidate the whole process. An empirical way to find the best number of clusters is to try K-means clustering with different number of clusters and measure the resulting sum of squares.

II.1.2 **Fuzzy c-means clustering:**

In fuzzy clustering, each point has a degree of belonging to clusters, as in fuzzy logic, rather than belonging completely to just one cluster. Thus, points on the edge of a cluster, may be in the cluster to a lesser degree than points in the center of cluster. For each point x we have a coefficient giving the degree of being in the kth cluster $u_k(x)$[10]. Usually, the sum of those coefficients for any given x is defined to be 1:

$$\forall x \left(\sum_{k=1}^{\text{num. clusters}} u_k(x) \ = 1 \right).$$

With fuzzy c-means, the centroid of a cluster is the mean of all points, weighted by their degree of belonging to the cluster:

$$\mathrm{center}_k = \frac{\sum_x u_k(x)^m x}{\sum_x u_k(x)^m}.$$

The degree of belonging is related to the inverse of the distance to the cluster center:

$$u_k(x) = \frac{1}{d(\mathrm{center}_k, x)},$$

then the coefficients are normalized and fuzzyfied with a real parameter m > 1 so that their sum is 1. So

$$u_k(x) = \frac{1}{\sum_j \left(\frac{d(\mathrm{center}_k, x)}{d(\mathrm{center}_j, x)} \right)^{2/(m-1)}}.$$

For m equal to 2, this is equivalent to normalizing the coefficient linearly to make their sum 1. When m is close to 1, then cluster center closest to the point is given much more weight than the others, and the algorithm is similar to k-means[10]. The fuzzy c-means algorithm is very similar to the k-means algorithm

II.2Thresholding Methods Thresholding is the operation of converting a multilevel image into a binary image i.e., it assigns the value of 0 (background) or 1 (objects or foreground) to each pixel of an image based on a comparison with some threshold value T (intensity or color value)[11].

When T is constant, the approach is called global thresholding; otherwise, it is called local thresholding. Global thresholding methods can fail when the background illumination is uneven. Multiple thresholds are used to compensate for uneven illumination. Threshold selection is typically done interactively.

There are numerous ways of selecting threshold like visual inspection, trial and error but these methods consume a lot of time .The best way for choosing threshold automatically is given in the following procedure [11]:

1.Select an initial estimate for T. Generally it is the midpoint .between the minimum and maximum intensity values of the image.
2.Segment the image using T. This will produce two groups of pixels: G1, consist of all pixels an image with intensity values ≥ T, and G2, consisting of pixels with values < T.
3.Then compute the average intensity values μ1 and μ2 for the pixels in regions G1 and G2.
4Last step is computing a new threshold value:

$$T = 1/2\ (\mu 1 + \mu 2)$$

Repeat the steps from 2 to 4 until the difference in T in successive iterations is smaller than a predefined parameter

II.3Edge Detection Methods Edge detection methods locate the pixels in the image that correspond to the edges of the objects seen in the image. The result is a binary image with the detected edge pixels. Common algorithms used are Sobel, Prewitt, Robert, Canny and Laplacian operators[12]. These algorithms are suitable for images that are simple and noise free; and will often produce missing edges, or extra edges on complex and noisy images.

II.3.1 Gradient Edge Detectors: It contains classical operators and uses first directional derivative operation. Itincludes algorithms such as: Sobel (1970), Prewitt (1970),Robert's operators. [12]

II.3.1.1 Laplacian of Gaussian (LoG):It was invented by Marr and Hildrethw (1980) who combined Gaussianfiltering with the Laplacian.This algorithm is not used frequently in machine vision. The Laplacian is a 2-D isotropic measure of the 2nd spatial derivative of an image. The Laplacian of an image highlights regions of rapid intensity change and is therefore often used for edge detection. The operator normally takes a single gray level image as input and produces another gray level image as output.

II.3.2 Gaussian Edge Detectors
This is symmetric along the edge and reduces the noise by smoothing the image. The significant Operators here are Canny which convolves the image with the derivative of Gaussian for Canny. The Canny edge detection algorithm is known as the optimal edge detector.[13]

These edge detection operators can have better edge effect under the circumstances of obvious edge and low noise. But the actual collected image has lots of noises. So many noises may be considered as edge to be detected. In order to solve the problem, wavelet transformation marked its presence to denoise the image.

II.4 Region-Based Methods The goal of region-based segmentation is to use image characteristics to map individual pixels in an input image to sets of pixels called regions that might correspond to an object or a meaningful part of one. The various techniques are: Local techniques, Global techniques and Splitting and merging techniques. The effectiveness of region growing algorithms depends on the application area and the input image. If the image is sufficiently simple, simple local techniques can be effective. However, on difficult scenes, even the most sophisticated techniques may not produce a satisfactory segmentation.[14].

Edge-based techniques are based on the assumption that pixel values change rapidly at the edge between two regions Operators such as Sobel or Roberts operators can be used to detect the edges. And some post procedures such as edge tracking, gap filling can be used to generate closed curves. Region based techniques are based on the assumption that adjacent pixels in the same region should be consistent in some properties. Namely, they may have similar characteristic such as grey value, color value or texture. The deformable models are based on curves or surfaces defined within an image that moves due to the influence of certain forces [13]. And the global optimization approaches use a global criterion when segmenting the image.

II.4.5 Water shed segmentation

A grey-level image may be seen as a topographic relief, where the grey level of a pixel is interpreted as its altitude in the relief. A drop of water falling on a topographic relief flows along a path to finally reach a local minimum. Intuitively, the watershed of a relief correspond to the limits of the adjacent catchment basins of the drops of water.

In image processing, different watershed lines may be computed. In graphs, some may be defined on the nodes, on the edges, or hybrid lines on both nodes and edges. Watersheds may also be defined in the continuous domain

II.4.5.1Meyer's flooding Watershed Algorithm

One of the most common watershed algorithms was introduced by F. Meyer in the early 90's.[15]

The algorithm works on a gray scale image. During the successive flooding of the grey value relief, watersheds with adjacent catchment basins are constructed. This flooding process is performed on the gradient image, i.e. the basins should emerge along the edges. Normally this will lead to an over-segmentation of the image, especially for noisy image material, e.g. medical CT data. Either the image must be preprocessed or the regions must be merged on the basis of a similarity criterion afterwards. [15]

1. A set of markers, pixels where the flooding shall start, are chosen. Each is given a different label.
2. The neighboring pixels of each marked area are inserted into a priority queue with a priority level corresponding to the gray level of the pixel.
3. The pixel with the highest priority level is extracted from the priority queue. If the neighbors of the extracted pixel that have already been labeled all have the same label, then the pixel is labeled with their label. All non-marked neighbors that are not yet in the priority queue are put into the priority queue. 4. Redo step 3 until the priority queue is empty. The non-labeled pixels are the watershed lines.

III. Evaluation and Comparison of Segmentation Techniques

In this work we have done a comparison of the output images after applying the specific algorithms. All the images are pre-processed using median filter. After pre-processing various discussed algorithms have been implemented using MATLAB and ImageJ. Images after segmentation are then assessed using performance parameters and the results are tabulated. Trials are done using images having different tumorsizes. The accuracy is also compared. The methodology followed is described in the following steps:-

1. Image acquisition: Obtain the original MRI images in digital form
2. Preprocessing of the image to improve the spectral quality
3. Implementation of the algorithm on the original image using image processing software such as MATLAB and ImageJ.
4. Obtain the output image after step 3 and note down the elapsed time

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5. Compute various performance parameters using appropriate formula(given in section 3) and record the values
6. Repeat the procedure using different images of varying tumor sizes for the different algorithms and create a comparison table.

III.1 Performance Parameters Calculated

The following performance parameters are calculated from the output image as referenced in step 5.The parameters are calculated by applying appropriate code that includes the formula for the computation. The parameters are calculated using software such as MATLAB and ImageJ.

A. MEAN SQUARE ERROR(MSE)

For an m*n image the MSE can be calculated as:

$$MSE = \frac{1}{m\,n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

Where I (i, j) is input image and K (i, j) is output image. The value of MSE should always be less than PSNR. Lower the value of MSE of an image means less error and high quality of the image. PSNR and MSE are inversely proportional to each other.

B. PEAK SIGNAL TO NOISE RATIO(PSNR)

$$\begin{aligned} PSNR &= 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\ &= 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \\ &= 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE) \end{aligned}$$

Higher the PSNR values, better the quality of image. If PSNR value is above 30, that means the output has hundred per cent image clarity. The unit of PSNR is dB (decibel). It takes from 0 to infinity[16].

C.ELAPSED TIME

Elapsed time is time taken to retrieve the segmented area from the input image. This method is calculated by tic and toc methods in mat lab.

D.MISCLASSIFICATION RATIO(MCR)

To measure the segmentation accuracy, we also define the misclassification ratio (MCR)[1], which is

$$\text{MCR} = \frac{\text{number of mis-classified pixels}}{\text{total number of pixels}},$$

E.ACCURACY

In numerical analysis, accuracy is the nearness of a calculation to the true value; while precision is the resolution of the representation, typically defined by the number of decimal or binary digits.

$$\text{accuracy} = \frac{\text{number of true positives} + \text{number of true negatives}}{\text{number of true positives} + \text{false positives} + \text{false negatives} + \text{true negatives}}$$

An accuracy of 100% means that the measured values are exactly the same as the given values[17].

IV. RESULTS

This section provides the experimental results after applying the specific algorithm using the methodology described in section 2.A sample input image in dicom format is shown below in figure 4. This image needs to be pre-processed and needs to be converted into a grey scale image.

Original DICOM image(Sample)

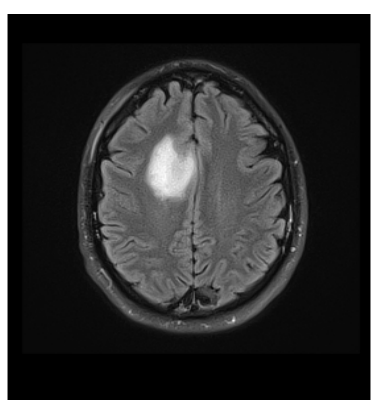

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Fig 4This is the MRI image of the cross-section of the brain in DICOM format. The above image may be subjected to segmentation to find if any tumor is present.

4.1Output images after application of various segmentation techniques along with the original image used

The section is divided into 3.Three images are taken of varying tumor sizes and are segmented individually. The image 1 has a large tumor,in image 2 medium size tumor is present and finally in image 3 we have a small size tumor.The results along with corresponding table and graphs are shown below.

Image 1(Tumor size:large)

Fig6(a) (b) (c) (d) (e) (f) (g)

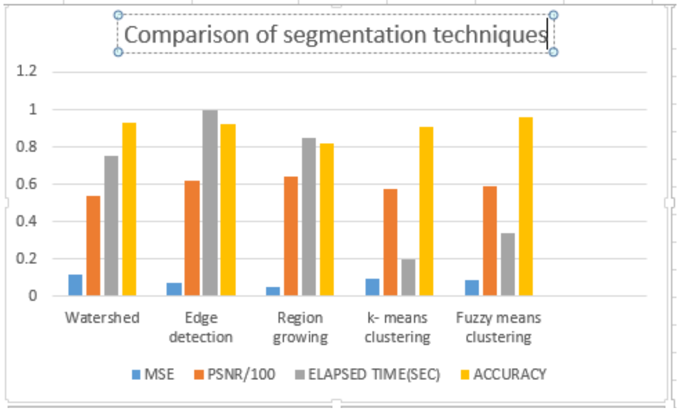
Fig6(a)original image(Image 1) followed by (b)watershed,(c)edge detection,(d)region growing(e) k means and (f)Fuzzy means clustering. The figure shows the original image along with the output image after the application of each algorithm for Image 1.

Comparison table 4.1

SEGMENTATION TECHNIQUE	MSE	PSNR	ELAPSED TIME(SEC)	ACCURACY(%)
Watershed	0.12	54	0.75	93
Edge detection	0.07	62.13	1	92
Region growing	0.048	64	0.85	82.28
k- means clustering	0.093	57.56	0.2	90.8
Fuzzy means clustering	0.086	59	0.34	95.7

Table 4.1 contains the segmentation technique along with the corresponding performance measures for image 1.The variations in PSNR and MSE can be easily understood. For Image 1. Fuzzy means clustering is the most suitable method for this image.

Graph 4.1



Graph 4.1: comparison of various methods for image 1

Graph 4.1 contains the segmentation technique along with the corresponding performance measures for image 1.The variations in performance measures are easily understandable from the graph.

Image 2(Tumor size:medium)

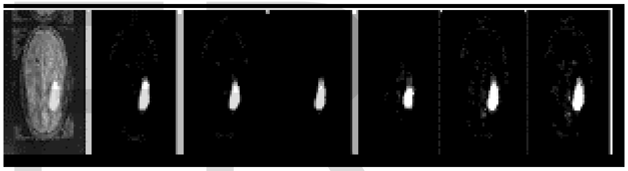


Fig7(a) (b) (c) (d) (e) (f) (g)

Fig7(a)original image(Image 2) followed by followed by (b)watershed,(c)edge detection,(d)region growing(e) k means and (f)Fuzzy means clustering The figure shows the original image along with the output image after the application of each algorithm for Image 2.

Comparison table 4.2

SEGMENTATION TECHNIQUE	MSE	PSNR	ELAPSED TIME(SEC)	ACCURACY(%)
Watershed	0.24	56	1	90
Edge detection	0.17	64	1.4	84
Region growing	0.088	67.58	1.12	82.28
k- means clustering	0.133	60	0.46	91
Fuzzy means clustering	0.096	66	0.58	87

Table 4.2 contains the segmentation technique along with the corresponding performance measures for image 1.The variations in PSNR and MSE can be easily understood. For Image 2. K means clustering may be the most suitable method for this image.

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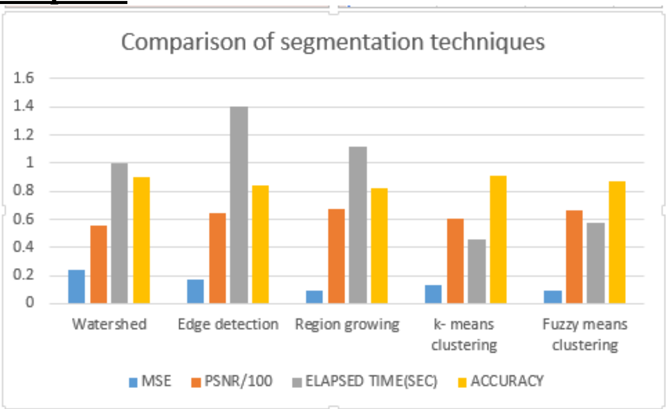
Graph 4.2



Graph 4.2:comparison of various methods for image 2

Graph 4.2 contains the segmentation technique along with the corresponding performance measures for image 2. The variations in performance measures are easily understandable from the graph

Image 3(Tumor size:small)

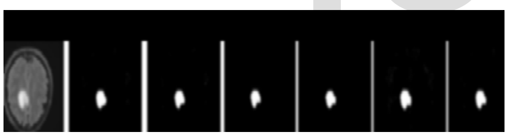


Fig8(a) (b) (c) (d) (e) (f) (g)

Fig8(a)original image(Image 3) followed by followed by (b)watershed,(c)edge detection,(d)region growing(e) k means and (f)Fuzzy means clustering

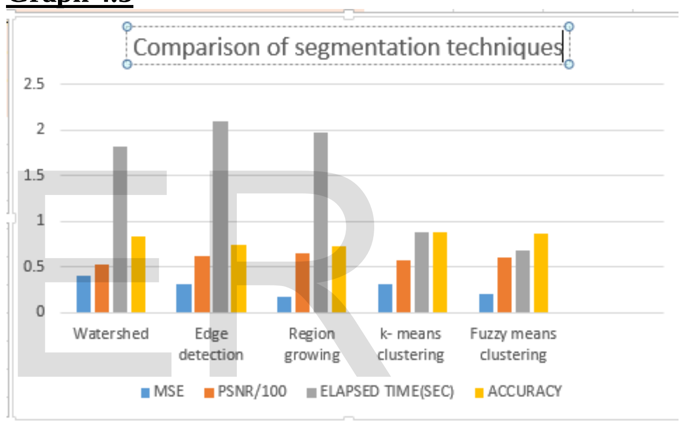
The figure shows the original image along with the output image after the application of each algorithm for Image 2.

Comparison table 4.3

SEGMENTATION TECHNIQUE	MSE	PSNR	ELAPSED TIME(SEC)	ACCURACY(%)
Watershed	0.4	53	1.82	83
Edge detection	0.31	62	2.1	75
Region growing	0.18	64.96	1.98	72.5
k- means clustering	0.31	57	0.88	88
Fuzzy means clustering	0.2	61	0.68	87

Table 4.2 contains the segmentation technique along with the corresponding performance measures for image 1.The variations in PSNR and MSE can be easily understood. For Image 3. K means clustering and Fuzzy means clustering provides optimum results for image 3 however latter may be preferred for lower MSE.

Graph 4.3



Graph 4.3 contains the segmentation technique along with the corresponding performance measures for image 3. The variations in performance measures are easily understandable from the graph.

V. CONCLUSION

The outcome of the application of each of the algorithm is greatly influenced by the type of image used for analysis. All algorithms do not generate same range of results for all kind of images. Specific algorithms needs to chosen depending on the input image used. From the comparative study that is conducted it is observed that even though the region growing algorithm is better for feature detection(Max PSNR) the speed of algorithm is quite lowwhich makes it difficult to use it for a large data sets. Also the accuracy of the method decreases greatly as tumor size varies. Watershed segmentationprovides good resultshowever needs thresholding as a prior step for good results and is better suited for images with greater contrast.K-means algorithm is faster and provides optimum results however it is lagging behind in preserving the edge features.The accuracy of the method is pretty much constant. This may be solved by appropriate steps taken in the pre-processing stage.A modified version of K-means algorithm may be used for large data sets which is under consideration for further study.Fuzzy means algorithm has greater accuracy for large feature-size(tumor) images however struggles with handling lower tumor sizes and a modified algorithm can provide better results.

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