Efficient T2 Brain Region Extraction Algorithm Using Morphological Operation and Overlapping test from 2D and 3D MRI images

Vandana J. Shah, Vijay S. Chaurasia, Ravindra V. Kshirsagar

Vandana J. shah is with the University of Nagpur, Research scholar, Nagpur, India,

Vijay S. Chaurasia is with the Manoharbhai Patel Institute of Engineering & Technology, Gondia, Maharashtra, India ,

Ravindra V. Kshirsagar is with the Priyadarshini Indira Gandhi College of Engineering, Nagpur, Maharashtra, India

Abstract*:* In the field of medical resonance image (MRI) processing the image segmentation is an important and challenging problem in an image analysis. The main purpose of segmentation in MRI images is to diagnose the problems in the normal brain anatomy and to find the location of tumour. Many of the algorithms have been found in recent years which aid to segment the medical images and identify the diseases. This paper proposes a novel 3D Brain Extraction Algorithm (3D-BEA) for segmentation of MRI images to extract the exact brain region. Transverse relaxation time (T2) weighted images are used as an input for the development of algorithm as these images provide bright compartments and dark fat tissues in the MRI brain region. The images are first denoised and smoothed for further processing. They are then used for extraction of irregular brain masks through threshold implementation which are then compared with the upper and lower slice of the brain images using morphological operations. The final brain volume has been generated using this 3D-BEA process. The result of this developed proposed algorithm is validated by comparing proposed algorithm with the results of the existing segmentation algorithm used for the same purpose. The proposed algorithm will help medical experts to understand and diagnose the tumour area of the patient.

Keywords*:* segmentation; morphological operations, clustering; k-means clustering; fuzzy c means clustering; Brain Extraction Algorithm.

1 Introduction

The main reason of image segmentation is to partition an input image into meaningful regions with respect to our particular application. The major significance of applying segmentation technique is to obtain coarse and fine details of tissues of brain MRI images in detail (Atkins and Mackiewich, 1998). Image segmentation is mainly used to detect objects and boundaries like lines, curves, edges etc. Image segmentation is the process of assigning a label to every pixel in an image which then assigned the same label who shares the same particular characteristics. The result of image segmentation is a set of segments that collectively cover the interested region in an image, or a set of contours extracted from the image (Gonzalez and Richard, 2007). Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic. The success or failure of computerized analysis procedure is specified by segmentation accuracy. The resulting contours after image segmentation of MRI images can be used to create 3D (Raya, 1990) reconstructions with the help of interpolation algorithms. Major applications of medical image processing are: detect and locate tumours and other pathologies issues (Brummer and Mersereau, 1993) measure tissue volumes, diagnosis, study of anatomical structure, surgery planning, virtual surgery simulation, and intra-surgery navigation.

In general, there are three important aspects to be considered in MRI image segmentation. The first aspect is the speed of the algorithm. The segmentation of image should not consume much time. The second aspect is good edge connectivity of its segmenting result (Perona and Malik, 1990). The third aspect is good shape matching. Consequently, it will be reliable (Somasundaram and Kalaiselvi, 2011). The limited disadvantages of segmentations could be fatal problem, the computation time and over segmentation. The result is sensitive to the selection of the initial random centroids in some of the segmentation techniques. Some region segmentation techniques can produce blocky segments.

There are three types of MRI brain images, but T2 image is giving more information for further Image processing and analysis as per the below information. Even the radiologist uses the T2 images for their analysis which is found in most of the MRI centres during research.

a. PD-weighted imaging is used to differentiate anatomical structures based on their proton density; i.e. the scanning parameters are set (long TR/short TE) to minimize T1 and T2 relaxation effects.

b. T1-weighted imaging is used to differentiate anatomical structures mainly on the basis of T1 values; i.e. the scanning parameters are set (short TR/short TE) to minimize T2 relaxation effects. Tissues with high fat content (e.g. white matter) appear bright and compartments filled with water (e.g. CSF) appears dark. This is good for demonstrating anatomy of any patient with brain tumour or without brain tumour.

c. T2-weighted imaging is used to differentiate anatomical structures mainly on the basis of T2 values; i.e. the scanning parameters are set (long TR/long TE) to minimize T1 relaxation effects. Compartments filled with water (e.g. CSF compartments) appear bright and tissues with high fat content (e.g. white matter) appear dark. This is good for demonstrating pathology since most (not all) lesions are associated with an increase in water content.

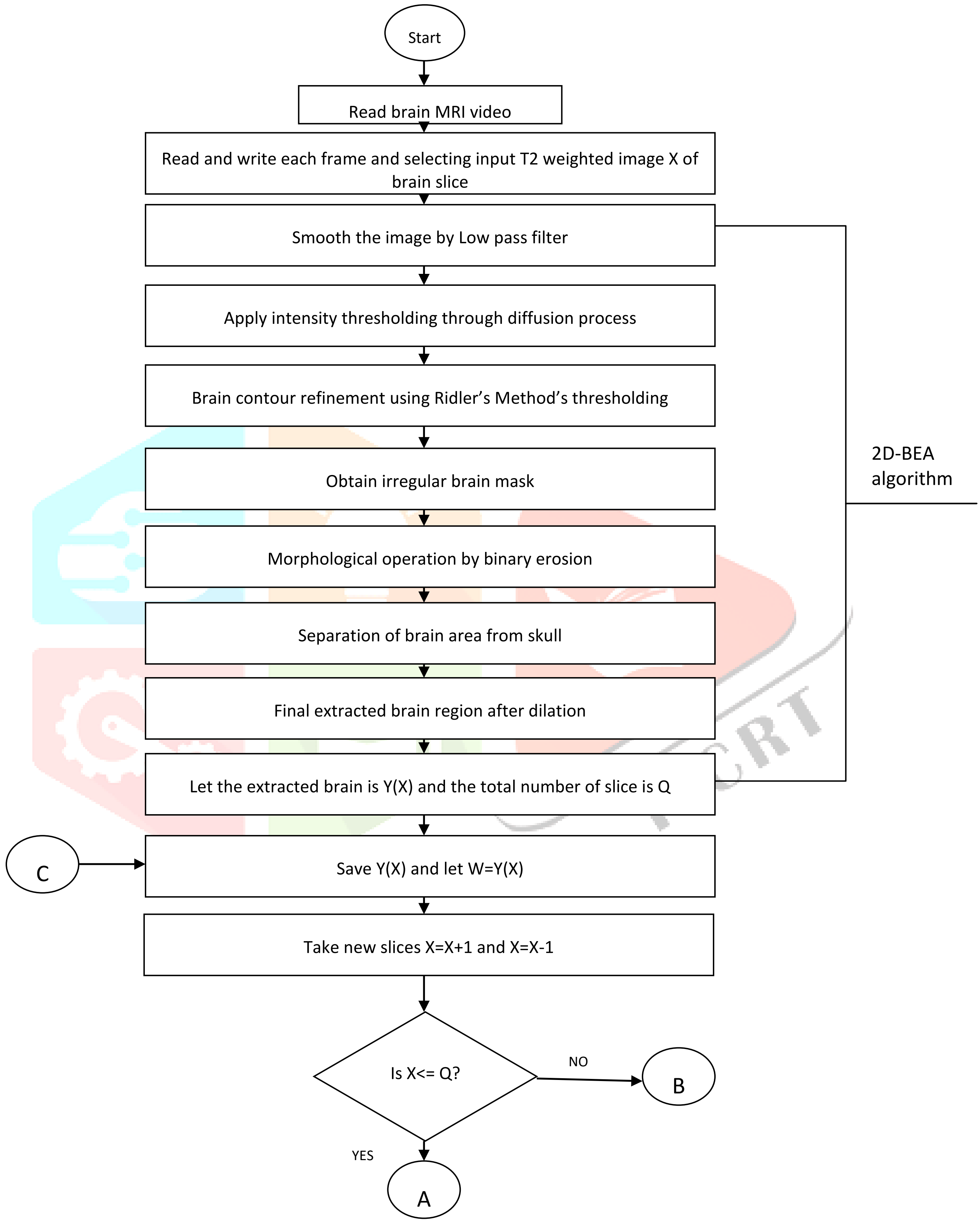
T1 relaxation is measured using a time constant called T1 (usually reported in milliseconds, msec). T1 is defined as the time when 63% of the longitudinal magnetization has recovered; 3 x T1=95% recovery. T2 relaxation is also measured using a time constant called T2 (usually reported in milliseconds, msec). T2 is also defined as the time when 63% of the transverse magnetization has decayed; 3 x T2=95% decay.

Radiologist are mainly using T2 weighted images for further analysis and there is the main reason that T2 weighted images are giving bright compartments as well as high fat tissues appears dark. So the main image for image processing would be T2 weighted image for further considerations.

Furthermore T2-weighted images are most sensitive for detecting brain pathology and human brain changes, patient with suspected intracranial diseases are to be first screened with T2 weighted MRI images.

Moreover MRI center at which the T2 weighted MRI images are processed they convert the DICOM image using Radiant Viewer 1.9.16 or EFILM or ISIRIX (if apple computer is used) software for processing the image and converting to JPEG image from DICOM as the DICOM image has very large size and could be difficult to process in the initial stage of the research. Nevertheless, it is really proper way out for analysing the MRI images in the DICOM format only and could be carried out in near future.3D-BEA is an essential pre-processing algorithm for several computer-aided brain processing techniques like brain tissue segmentation, brain tumour/lesion detection, brain image compression and registration. This algorithm helps to speed up and produce accurate results for the computer aided diagnosis. Several popular and existing brain extraction algorithms are commonly focused on T1-weighted scans and were failed to work for T2-weighted brain MRI images. Moreover as per the research it has been found that other BEAs are failed in indentifying Largest Connected Components. These limitations have been overcome in proposed 3D-BEA algorithm.

Accurrate brain region extraction of the MRI brain image is challenging due to poor MR image segmentation and can lead to overestimation of the segmented brain. These technical challenges have resulted in a limited number of studies for image segmentation for Brain MRI images. This study proposes a novel methodology for removing skull area and extracting only brain region. Total 50 adult pateints images had been collected for extracting only interested region of the brain from input viedo recording. Proposed methodology suggested to consider the data that was actually acquired in clinical practice for any image based studies and not to have a post-processing that will influence clinical image acquisition practice significantly. Hence the neighborhood operations involved in our method like filtering, diffusion process, morphological operations and connected com- ponent analysis are strongly implemented in 3D Brain MRI operations. The third dimension (3D) of the image is used to ensure that the component extracted is a brain portion by performing an overlap test between adjacent slices.


Start
Read brain MRI video
Read and write each frame and selecting input T2 weighted image X of brain slice
Smooth the image by Low pass filter
Apply intensity thresholding through diffusion process
Brain contour refinement using Ridler's Method's thresholding
Obtain irregular brain mask
Morphological operation by binary erosion
Separation of brain area from skull
Final extracted brain region after dilation
Let the extracted brain is Y(X) and the total number of slice is Q
2D-BEA algorithm
C
Save Y(X) and let W=Y(X)
Take new slices X=X+1 and X=X-1
Is X<= Q?
NO
B
YES
A

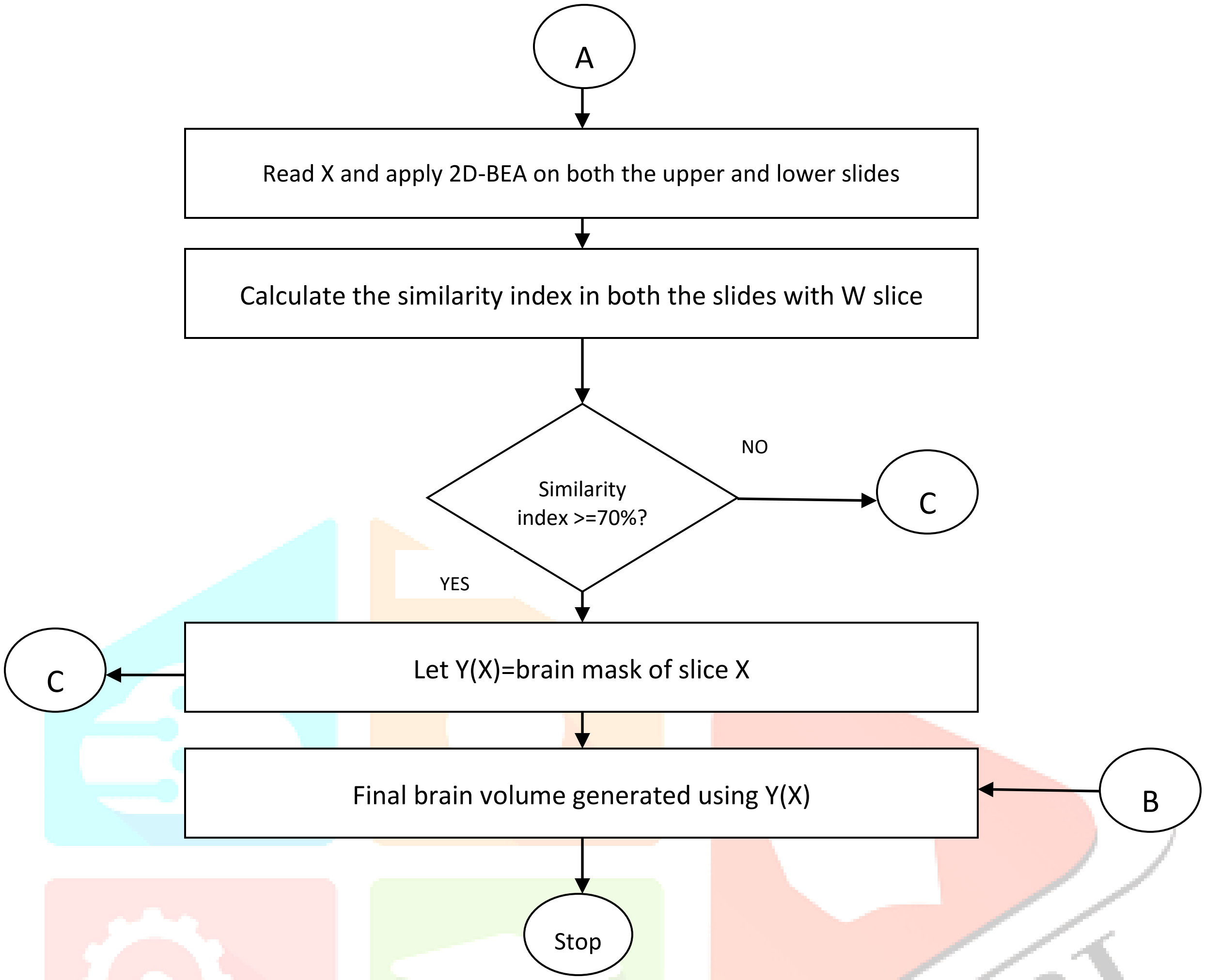


Figure 1 Proposed technique for 3D-Brain Region Extraction of T2 weighted brain MRI image

2 Proposed Algorithm for 3D-Brain Region Extraction

The main purpose of the flow chart shown in figure 1 is to detect the region of brain with many pre-processing steps. The input MRI image is in JPEG form which selects one of the slices from more than 100 slices of a single patient's data. That has to be T2 weighted image for fine analysis of the brain.

Before finding tumour it is important to segment the region of interest. Over here the region of interest is only brain area which has to be removed from skull. 2D-BEA is one of the techniques which extract the brain area from skull and boundary.

In 2D-BEA first of all in the first stage the background noise from the brain image will be removed using low pass filter and the output is further diffused to enhance the brain boundaries. This will be forwarded by thresholding in which mask for the coarse brain is generated. In the second stage, morphological based segmentation operation is performed with connected component analysis to extract the fine brain from the coarse brain portion obtained in first stage of 2D-BEA.

As per the figure 1, the segmented brain region will be further given to 3D-BEA because the 2D-BEA has limitation for largest connected component identification (Somasundaram and Kalaiselvi, 2011). 3D-BEA may remove that limitation and could be implemented for further research. The method makes the use of geometric continuity of the brain region to extract the overall brain region.

The method makes the use of following steps to extract the exact brain region from the above algorithm of 3D-BEA.

Step 1: Initially MRI T2- weighted image t(x, y) is smoothed using Low Pass Filter (LPF) with a structuring element (STEL) as a morphological operation. LPF is given by equation 1,

$L_p(u,v)$= H(u,v)T(u,v)……………………………(1)

Where, T(u,v) shows the Fourier transform of input T2 weighted image t(u,v), H(u,v) is the transform function of LPF, the filtered image is obtained simply by taking inverse Fourier transform as shown in equation 2.

I(x,y)= IFT(L_p(u,v))..……………………………..(2)

Construction of LPF convolution template is given by equation 3.

(1/9)*[1 1 1; 1 1 1; 1 1 1]………………………...(3)

f2=imfilter(f1,lpf);
In the above equation the convolution matrix has been used which later is processed by MATLAB command imfilter for smoothing the input image.

Step 2: After above step the diffusion process is applied on filtered image for removing blurriness in the image.
This process is calculating gradient in North, South, east and West direction using convolution mask as shown in below equations 4 to 7 respectively.

hN=[0 1 0; 0 -1 0; 0 0 0]…………………………(4)
hE=[0 0 0; 0 -1 0; 0 1 0]…………………………..(5)
hS=[0 0 0; 0 -1 1; 0 0 0]…………………………..(6)
hW=[0 0 0; 1 -1 0; 0 0 0]…………………………..(7)

Step 3: Binarization of the diffused image I(x,y) has been generated using Riddler's thresholding method; where two means has been calculated. i.e. μ_0 and μ_1 are the means of each of the two components of the histogram separated by the initial value of threshold. This is calculated as below equation 8;

T(i)= (μ_0 + μ_1)/2…………………………………..(8)

Continuous iteration has been carried out to find the final threshold value using below equation.
T_{final}=tvalue; where tvalue is given by below equation 9.
tvalue=T(i) for abs(T(i)-T(i-1))>=1 condition must be satisfied.………………………………………………
…...(9)

For final binarization if the pixel value is greater than tvalue then '1' is assigned to that pixel otherwise '0' is assigned to the same pixel.
Step 4: After getting binarized image using Riddler's threshold method the morphological operation has been performed to eliminate unwanted region. This uses a proper structuring element (STREL). The erosion has been processed for the same task using below equation 10.

I_1=I_{old} θ X_1………………………………….……(10)

Where I_{old} is the binarized image and X_1 is wide enough to detect the eye portion and detach the eyes with other small structure from the brain in axial scans. The final eroded image is I_1. After this imopen command of MATLAB has been used to achieve image I_2 for removal of unwanted minute regions. This process is further gone through the dilation morphological operation using below equation 11.

I_3= $I_2 \oplus X_1$………..………………………………(11)

Where I_3 shows the dilated image with boundary strengthening which was lost during erosion. The brain area selection has been processed by finding Largest Connecting Component.

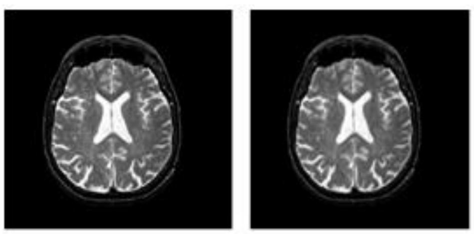
Step 5: After applying 2D-BEA the extracted brain region is noted by Y(X) and the total number of slices for the same patient is considered as Q. This Y(X) will also be stored in some temporary register. Two slices will be compared with Y(X). i.e upper slice X+1 and lower slice X-1.
Step 6: If this comparison is greater than some threshold value (here it is 70%), then it will be considered as final extracted brain region else we consider the (X-1) and (X+1) images both together and repeat the previous steps number 2 to 4.

The scalp-skull boundaries are very weak in T2-weighted images (Somasundaram and Kalaiselvi, 2011) and hence0020they are not preserved. In 2D-BEA as shown in below figure 1, the diffusion process helps to compute an intensity threshold value automatically to segment the brain from non-brain tissues. Thus stage one is preserving brain borders. Thresholding helps to produce the rough mask brain. In the second stage main shape characteristics of object will be identified. Erosion and dilation produced the curve boundaries of brain regions of binary image.

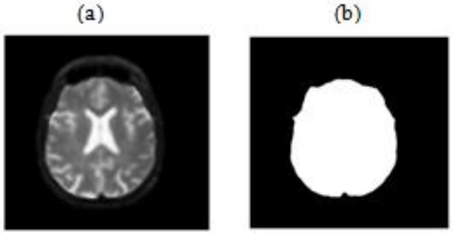
3 Implementation and experimental results for the Proposed Algorithm

The implementation of the developed algorithm is carried out by considering images from real patient suffering from brain tumour and medically treated at “Chhaydo MRI center” at Surat city. The images have been collected from Dr. Vinay Shah, the radiologist of the same MRI center with prior permission at city surat and state Gujarat. After collecting these images the work has been carried out for image segmentation (N. Sathya, 2017) and brain region extraction as per the steps shown in algorithm. Moreover it has also been verified by the same doctor for validation and further process.

As per the different steps of the algorithm below figure 2 shows the step wise result of implementation for same patient’s T2 weighted image. Moreover figure 3 is showing the different slices of the same brain regions in the extracted form. It has been observed that more efficient output is achieved in the 3D-BEA with the exact brain region extraction.

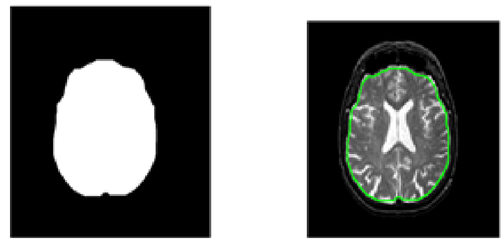


(a) (b)

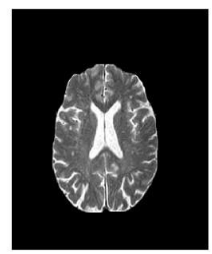


(c) (d)

(e) (f)



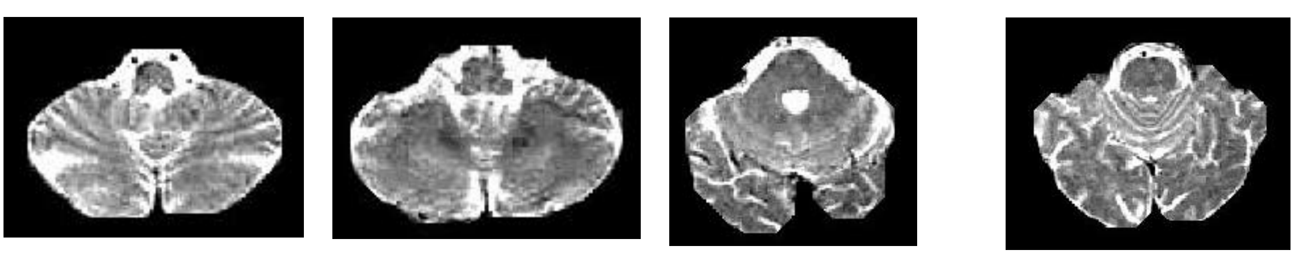
(g) (h)



(i)

Figure 2 Extracted brain region using 2D-BEA algorithm for T2 Weighted images (a) Original image (b)LPF image(c) Diffused image(d) Binarized image (e) Eroded image (f) Horizontal structuring element (g) Disk structuring element (f) Brain region in the main brain image (i) Extracted brain region

The results in figure 2 shows that using 2D-BEA method the interested brain region is extracted and it removes the unwanted area like skull and other boundaries. It is fulfilling the main purpose of finding out the different possible locations of tumour for the later research.



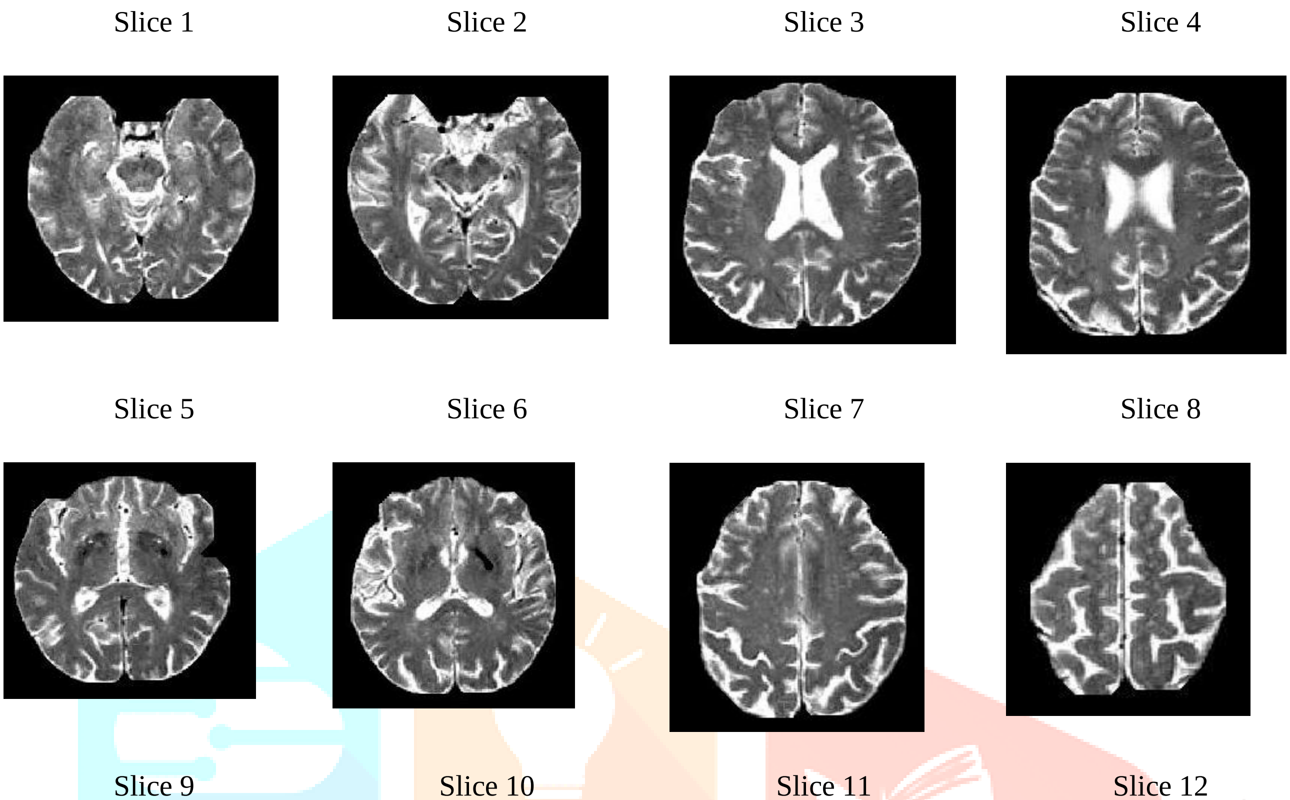


Figure 3 Extracted brain region using 3D-BEA algorithm for T2 weighted images

4 Comparative analysis of developed algorithm with different segmentation techniques for MRI brain images

In addition to the analysis of developed algorithm, the comparative analysis is also carried out with the existing algorithms. It would be easy to identify the efficient algorithm after this analysis. In this section total five segmentation algorithms have been implemented. Mainly cluster based algorithms are compared to validate developed algorithm. Below shows the algorithms and their steps with their importance in different aspects.

4.1 Fuzzy c means based clustering

Fuzzy c-means algorithm allows data to belong to two or more clusters with different membership coefficient. Fuzzy C-Means clustering is an iterative process. First, the initial fuzzy partition matrix is generated and the initial fuzzy cluster centers are calculated. In each step of the iteration, the cluster centers and the membership grade point are updated and the objective function is minimized to find the best location for the clusters. The process stops when the maximum number of iterations is reached, or when the objective function improvement between two consecutive iterations is less than the minimum amount of improvement specified (Ajala, 2012).

$$J = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \left(\sum_{j}^{n} u_{ijm} \; d(X_j - C_i) \right) \text{.............(12)}$$

Where, J = Cost Function

Ji = Cost of the ith Cluster

$\sum_{j}^{n} u_{ijm}$ = fuzziness exponent

d(Xj-Ci) =Distance form point to nearest centroid.

Moreover the update in the iteration is done using the membership degree as well as the centre of the cluster that is the two parameter change as the steps are being repeated until a set point called the threshold is reached or the process stops when the maximum number of iterations is reached, or when the objective function improvement between two consecutive iterations is less than the minimum amount of improvement specified. In addition a fuzziness coefficient 'm' is chosen which may be any real number greater than 1(Benjamin, 2012).

Below shows the algorithm steps of Fuzzy c means (Selvalakshmi, 2017).

Step 1: Initialize the membership Matrix
Step 2: Calculate the degree of membership
Step 3: Compute the centroid and update the new membership and Recalculate the degree of membership
Step 4: If the difference of centroid matrix between new and previous iteration is less than the predefine value then recalculate the degree of membership.

4.2 K-means clustering

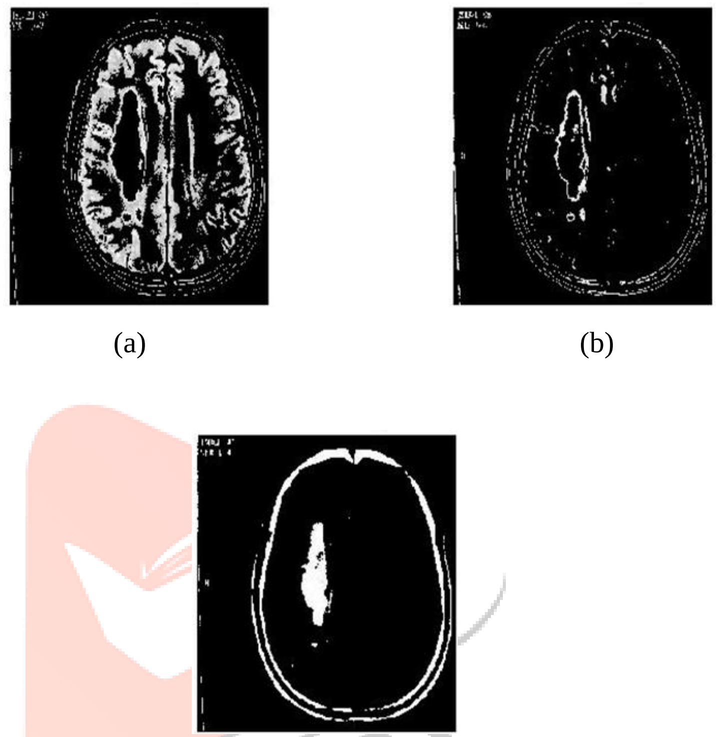
It is one of the easiest methods of unsupervised learning algorithm that solve the well-known clustering issue (Funmilola and Adedeji, 2012). K-means is purposed by Macqueen in 1967. K-means is a simple clustering method which is having low computational complexity as compared to Fuzzy C-means. K-means clustering do not overlap the clusters.

$$J = \sum_{i=1}^{c}\left(\sum_{k, X_k \in G_i} d(X_k - C_i)\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (13)$$

Below shows the algorithm of k means clustering algorithm for MRI brain image segmentation.

Step 1: Select K points as the initial centroids.
Step 2: Repeat
Step 3: Form K clusters by assigning all points to the closest centroid
Step 4: Recompute the centroid of each cluster.
Step 5: Until the centroids don't change.

Simplicity and easy implementation are some advantages of k-means but it has several drawbacks as well. There is no standard for a good set of initial centres. Instead of random choices, initial k-means results can provide the initial points for the next run of the algorithm.



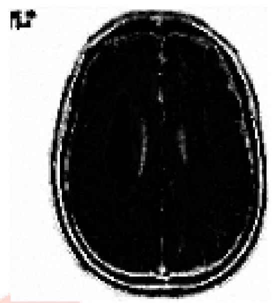
(a) (b) (c)

Figure 4 K means clustering based segmentation (a) Cluster 1, (b) Cluster 2, (c) Cluster 3

(a)

(b)

(c)



(d)

Figure 5 Fuzzy C Means clustering, (a) Cluster 1, (b) Cluster 2, (c) Cluster 3, (d) Cluster 4.

TABLE 1 Comparison of different image segmentation techniques for MRI images of brain

Parameter	Fuzzy C-Means	K-Means	Brain Extraction algorithm 2D-BEA	Brain Extraction algorithm 3D-BEA
Noise	Cannot remove noise	Cannot remove noise.	Removing the noise by filtering.	Removing the noise by filtering.
Smoothing	Doesn't smooth the image	Different initial centroids will bring about the different results.	More Smoothed image is produced.	More Smoothed image is produced.
Separation	Used for MRI image segmentation	Other region can also separate.	Can separate unwanted area like skull but not efficiently	Can separate unwanted area like skull as it is best for Largest connecting component identification
No. of Cluster	Apriori Specification of the number of cluster	A problem of choice of numbers of cluster N.	Does not require prior knowledge of the number of clusters.	Does not require prior knowledge of the number of clusters.

Over segmentation	Does not over segmented image.	Does not over segmented image.	Does not over segmented image.	Does not over segmented image.
Time of execution	12.539335 seconds*.	14.116299 seconds*.	8.732305 seconds*.	76.019408 seconds.

*Time of execution shown in the comparison table is the duration of the algorithms implemented by the authors of this research paper.

Above table 1 depicts the importance of proposed algorithm 3D-BEA in all aspects towards better segmentation of brain MRI images. As compared to other segmentation algorithms searched by previous researchers the 3D-BEA algorithm is removing noise from the input image with limitations in computational time. Proposed algorithm is also efficient to identify the smooth edges as well as preserving information. This developed algorithm does not over segment the image so that blur effect comes down to null. Moreover it is so user friendly and automated that it does not expense time to diagnose unwanted area and only extract the desire region of brain MRI images.

As per the figure 1 in paper, the segmented brain region will be further given to 3D-BEA because the 2D-BEA has limitation for largest connected component identification. The concept of Largest connected component failed in few slices in 2D-BEA and other previous algorithms. Previous researcher's algorithms carried out single algorithm strategy which later found to perform less satisfactory than hybrid strategies shown in 3D-BEA. 3D-BEA may remove that limitation and could be implemented for further research. The method makes the use of geometric continuity of the brain region to extract the overall brain region. The past algorithm are based on 2D-BEA which is already mentioned in the paper and by the research implementation it is found the 3D-BEA algorithm is considering all slides of the patient for identifying Largest Connected Component. Furthermore with this concept there is no such algorithm found by previous researchers. The comparison is made with only 2D-BEA.

Medical Resonance Image segmentation is very essential feature in most of image processing methods, which reflects anatomical structure of segment (brain tissue). The usefulness of these methods in clinical environment significantly depends on the ease of computation and the reduction of human intervention. The proposed method is based on histogram based gradient calculation, which segments out primary objects from T2 brain MR image (Gilanie and Attique, 2013). The applicability of this algorithm has been practically verified giving satisfactory results. It is established that the proposed method can be applied on other medical imaging modalities or other image processing domains and is quite efficient.

5 Conclusion

Brain extraction algorithm is a general category of algorithms used to extract/evaluate features of a given brain scan. It also performs the very same task of post processing. In first stage, coarse brain is generated using filtering and thresholding. In second stage, morphological operations performed on binary image to segment the fine brain mask. It has been observed from the comparative analysis that existing methodology of segmentation is not able to remove noise as well as blur the images and moreover it does not extract brain area which is the main interest for further research and for finding out the tumour in the later stage. In future to overcome the failure of 2D-BEA, 3D-BEA will be used. For the current research the partial algorithm of proposed technique has been implemented. Further study will be taken up in near future for image classification and other pre-processing. Results show the validity of the 3D-BEA algorithm and its advantages through comparison.

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Vandana J. Shah received her master research in VLSI technology from Nagpur University, India in 2012. She is currently a researcher in medical field for MRI brain tumour analysis and pursuing her PhD in Department of Electronics from the Nagpur university, her current research interest include, the computer assisted brain anatomy analysis and image segmentation techniques.

Vijay S. Chourasia is working as an Assistant Professor in the Department of Electronics and Communication Engineering at Manoharbhai Patel Institute of Engineering and Technology, Gondia, India. He obtained his PhD from The LNM Institute of Information Technology, Jaipur. He has more than 25 years of experience in the field of academics and has about 35 research publications in various international and national journals and conferences. His research interest is Signal and Image Processing.

Ravindra V. Kshirsagar is working as a professor in the Department of Electronics Engineering at Priyadarshini College of Engineering (PCE) and Vice Principal at PCE, Nagpur. He is also the former-dean of Nagpur University.

He obtained his Ph.D. from VNIT, Nagpur in sept’2010. He has a vast teaching experience of 27 years and 2 years of industry experience. He has published many research papers in national and international conferences. His special field of interest includes Reconfigurable Computing, VLSI Design, Fault tolerance and DFT.