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# MRI Fuzzy Segmentation of Brain Tumor with Fuzzy Level Set Optimization

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***ABSTRACT: Image segmentation is a task that is fundamental many image processing and computer vision applications. Due to the existence of noise, low contrast, and intensity in homogeneity, it really is still a difficult issue in majority of applications. One of the steps that are first way of understanding images is to segment them in order to find down different objects inside them. However, in real images such as MRI graphics, noise is corrupting the image information or image usually consists of textured sections. The images produced by MRI scans are frequently grey images with strength in the product range scale that is gray. The MRI image associated with the brain comprises of the cortex that lines the surface that is outside of brain additionally the gray nuclei deep inside of the mind including the thalami and basal ganglia. As Cancer may be the leading cause of death for all as the explanation for the condition remains unknown, very early detection and diagnosis is one of the keys to cancer control, and it will increase the success of treatment, save lives and reduce expenses. Health imaging is very often used tools which can be diagnostic detect and classify defects. To eliminate the dependence of the operator and increase the precision of diagnosis system aided diagnosis computer are a valuable and ensures that are advantageous the detection of cancer tumors and classification. Segmentation techniques based on gray level techniques such as for instance threshold and methods based on region are the easiest and find application that is restricted. However, their performance can be improved by incorporating them with the ways of hybrid clustering. practices based on textural characteristics atlas that is using look-up table can have very good results on the segmentation of medical pictures , however, they require expertise within the construction of the atlas Limiting the technical atlas based is that , in some circumstances , it becomes difficult to choose correctly and label information has difficulty in segmenting complex structure with variable form, size and properties such circumstances it is best to use unsupervised methods such as fuzzy algorithms. In this work we proposed a novel fuzzy based MRI Image Segmentation algorithm, Fuzzy Segmentation involves the task of dividing data points into homogeneous classes or clusters making sure that things within the same class are as similar as possible and items in numerous classes are as dissimilar as you can.***

## 1. INTRODUCTION

Image segmentation [8] is a vital scrutiny span because it plays a frank act in picture scrutiny, and understanding. Segmenting a picture is the most challenging and tough task because there continue disparate objects and a huge variations amid them employing a finished framework. With the advent of present publishing technologies, the layout of today's documents has not ever been extra complex. Most of them encompass not merely text and background spans, but additionally graphics, tables and pictures.

## 1. Digital image processing

"Image is an intellectual and emotional convoluted in an instant of time". The word Image, mentions to a two-dimensional light intensity purpose f(x, y),where x and y are spatial coordinates, and the amplitude of f at each pair of coordinates (x, y) is shouted the intensity or gray level of the picture at that point. Whereas x, y and the amplitude benefits of f are all finite, discrete numbers, we call the picture as digital image.Though, one functional paradigm is to ponder three kinds of computerized procedure in this continuum: low-level, mid-level and high-level processes.

Low-level procedures involve primitive procedures such as picture processing to cut sound, difference enhancement, and picture sharpening. A low-level procedure is described by the fact that both its inputs and outputs are images. Mid- level procedures on pictures involve tasks such as segmentation (partitioning an picture into spans or objects), description of those objects to cut them to a form suitable for computer processing, and association (recognition) of individual objects. A mid-level procedure is described by the fact that its inputs usually are pictures, but its outputs are qualities removed from those pictures (e.g., borders, contour, and the individuality of individual objects).

Finally, higher-level processing involves "making sense" of an ensemble of understood objects, as in picture scrutiny, and at the distant conclude of the continuum, giving the cognitive purposes normally associated alongside human vision.

**Output of these processes generally is images**

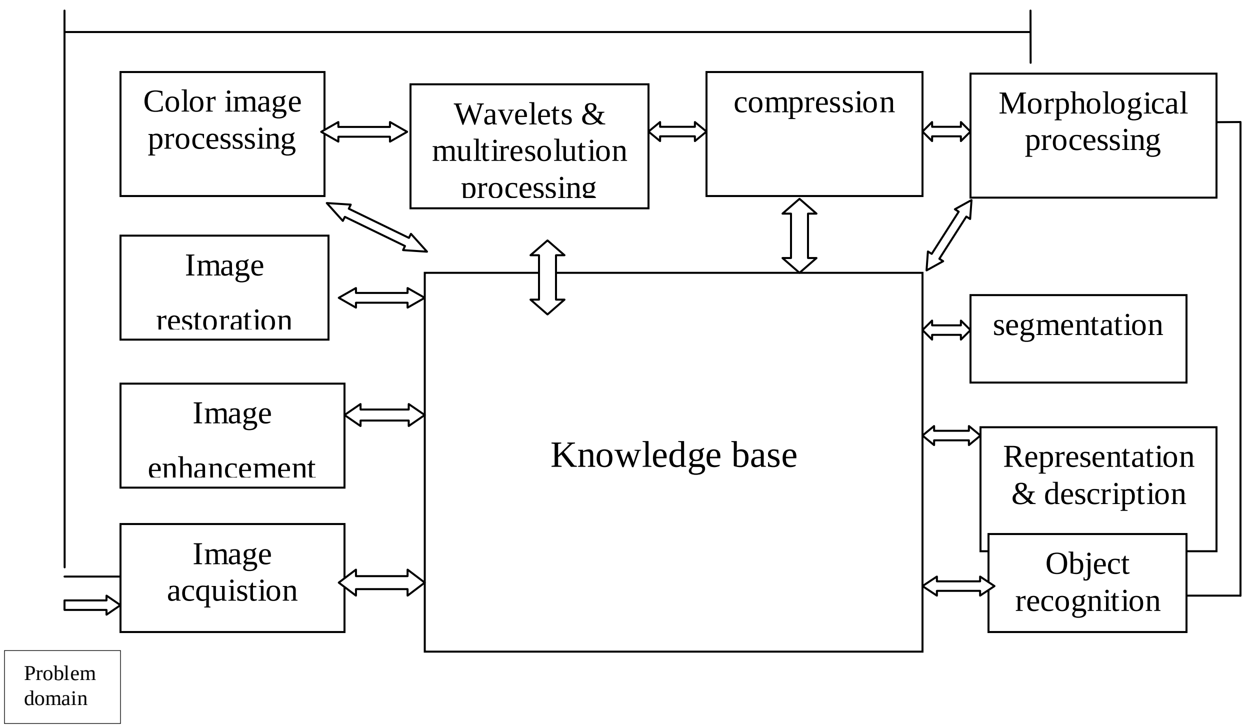



**Figure 1.1 Fundamental steps of image processing**

**Digital image properties**

A digital picture has countless properties, both metric and topological, that are somewhat disparate from those of constant two-dimensional purposes alongside that one can acquainted from frank calculus. One more feature of difference is human understanding of pictures, as judgment of picture quality is additionally important.The distance between points with co-ordinates $(i, j)$ and $(h, k)$ may be defined in several different ways; the *Euclidean distance* $D_E$ known from classical geometry and everyday experience is defined by

$$D_E[(i, j), (h, k)] = \sqrt{(i-h)^2 + (j-k)^2}$$

Pixel adjacency is one more vital believed in digital images. Each two pixels are shouted 4-neighbors if they have distance D4=1 from every single other. Analogously, 8-neighbors are two pixels alongside D8=1. 4-neighbors and 8-neighbors are illustrated in Figure.1.2

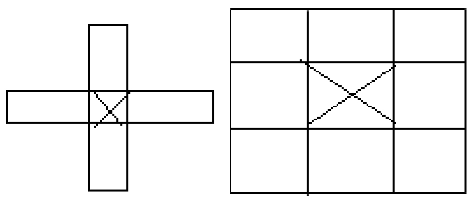


**Figure 1.2 Pixel neighborhood**

i. **Contrast:** Contrast is the innate change in brightness and is described as the ratio amid average brightness of an object and the background brightness. The human eye is logarithmically sensitive to brightness, implying that for the a like understanding, higher brightness needs higher contrast.
ii. **Acuity:** Acuity is the skill to notice features in the image. The human eye is less sensitive to sluggish and fast adjustments in brightness in the picture plane but is extra sensitive to intermediate changes.
iii. **Object border:** Object borders hold a lot of information. Borders of objects and easy outlines such as blobs or lines enable adaptation results comparable to conditional difference, remarked above.
iv. **Image quality**: An picture could be degraded across arrest, transmission, and measures of picture quality can be utilized to assess the degree or degradation. The quality needed naturally depends on the intention for that an picture is used.
v. **Noise:** Real pictures are frequently degraded by a little random errors-this degradation is normally shouted noise. Sound can transpire across arrest, transmission, or processing, and could be reliant on, or autonomous of, picture content.

**Fuzzy C-Means Algorithm for Segmentation**

In this section, we give a brief overview of the standard FCM clustering algorithm. It was first introduced by Dunn and later extended by Be zdek. Its objective is to partition data in such a way that the data points within one cluster are as similar to each as possible and as far away as it can be from the data points of other clusters. In the context of our work, the FCM approach can be formulated as follows. For each point $i \in N, let\ (u_{ic})_{c=1}^{k} = (u_{ij}, u_{i2}, \dots \dots, u_{ik})$be the memberships of the point i with respect to these K classes, such that$\sum_{c=1}^{k} u_{ic} = 1\ and u_{ic} \in [0,1]$. For each class c let vs. is the centric (class center) of this class (this usually corresponds to the mean value of this class's points). In the FCM approach, the segmentation process of the image (volume) can be defined as the minimization of the energy function

$$J_{FCM} = \sum_{C=1}^{K} \sum_{i=1}^{N} u_{ic}^{m} \parallel y_i - V_c \parallel^2$$

The parameter m is a weighting exponent on each fuzzy membership and determines the amount of fuzziness of the resulting classification (typically set to 2). This function in can be easily minimized using the Lagrange multiplier (λ), so the constrained optimization becomes

$$F_{FCM} = \sum_{C=1}^{K} \sum_{i=1}^{N} u_{ic}^{m} \parallel y_i - V_c \parallel^2 + \lambda(1 - \sum_{c=1}^{K} u_{ic}).$$

A solution can be obtained by alternatively computing the membership ratios uic and the centroids vc until convergence as follows:

$$v_c = \frac{\sum_{i=1}^{N} u_i^2 y_i}{\sum_{i=1}^{N} u_{ic}^2},$$

$u_{ic} = \frac{1/d_{ic}}{\sum_{j=1}^{K} 1/d_{ij}}$, Where $d_{ic} = \parallel y_i - vc \parallel$.

The memberships are often initialized with random values between 0 and 1, such that the constraint of the membership is satisfied. The FCM objective function is minimized when high membership values are assigned to points whose intensities are close to the centric of its particular class, and low membership values are assigned when a point's intensity is far from the centric.

PROPOSED WORK:

**Improved FCM :**The proposed approach reformulates the popular fuzzy c-means (FCM) algorithm to take into account any available information about the Energy Levels. The uncertainty in this information is also modeled. This information serves to regularize the clusters produced by the FCM algorithm thus boosting its performance under noisy and unexpected data acquisition conditions. Image is transformed into feature space, stop condition ε, fuzziness parameter m . Let X={$x_1, x_2, \ldots, x_n$} into a collection of c fuzzy clusters with respect to some given criterion. Given a finite set of data, the algorithm returns a list of c cluster centers V, such that V = $\boldsymbol{v_i | i = 1, 2 \ldots c}$

and a partition matrix U such that **U = $U_{ij}$, i =1, ..., c, j =1,..., n**

Where $U_{ij}$ is a numerical value in [0, 1] that tells the degree to which the element $x_J$ belongs to the $i^{th}$cluster.

**Step 1**: Repeat for each pixel $a_{ij}$ of image X.

**Step 2**: Select the number of clusters

$$C, 2 \leq C \leq n,$$

Exponential weight

$$\mu \ (1 < \mu < \infty),$$

Initial partition matrix $U^0$, and the termination criterion ∈. Also, set the iteration index l to 0.

**Step 3**: Calculate the fuzzy cluster centers $\{\boldsymbol{V_i^1\ i = 1, 2 \ldots c}\}$ **using $U^1$**

**Step 4**: Calculate the new partition matrix $\boldsymbol{U^{i+1}}$

$$\{\boldsymbol{U_i^1\ i = 1, 2 \ldots c}\}$$

**Step 5**: Find out, whether in the closest surroundings of pixel $a_{ij}$ exists segment, which points belong to same cluster center C and partition matrix $U_i$ based on Energy of Pixels.

**Step 6:** Merge all Fuzzy segments which belong to one cluster center.

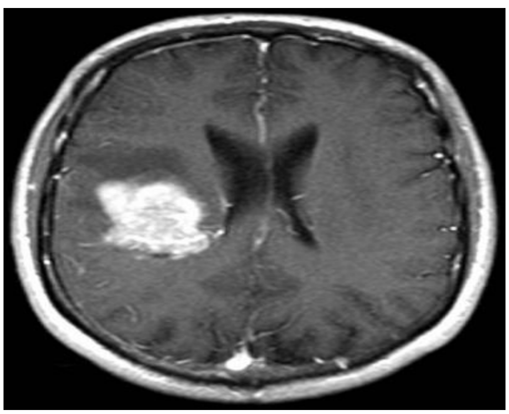
**Step 7:** Calculate the new partition matrix, for next iteration of segmentation

$$\Delta = \left|U^{i+1} - U^{i}\right| = max_{ij}\left|U_{ij}^{i+1} - U_{ij}^{i}\right|$$

**Step 8**: if $\Delta > \epsilon$ then, set i = i + 1, and recalculate Fuzzy cluster centers.

**Step 9:** if $\Delta \leq \epsilon$ Terminate

Results and Analysis: Brain tumor segmentation process consists of separating the different tumor tissues, such as solid tumor, edema, and necrosis from the normal brain tissues, such as gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF). Although manual segmentation by qualified professionals remains superior in quality to automatic methods, it has two drawbacks. The first drawback is that producing manual segmentations or semi-automatic segmentations is extremely time-consuming, with higher accuracies on more finely detailed volumes demanding increased time from medical experts. The second problem with manual and semiautomatic segmentations is that the segmentation is subject to variations both between observers and within the same observer. In this work we have tried to improve the Semi-automatic Gray Matter based Segmentation process using Energy levels of the Image. Many GM MRI images where taken for analysis using the improved FCM algorithm, the results are described below:



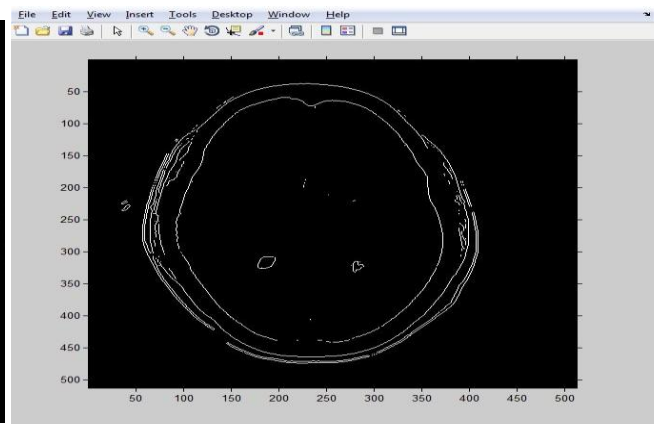
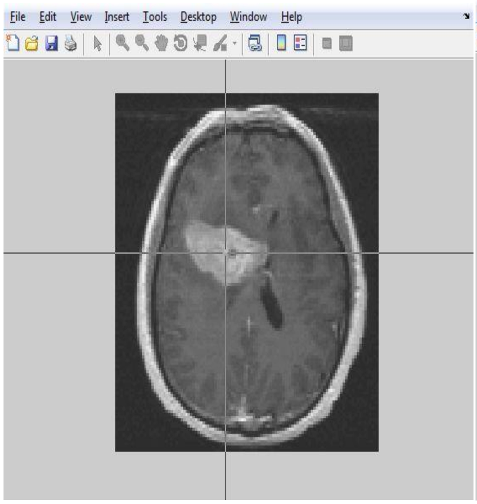



**Fig 5.5:Sample Brain Tumor taken from MRI Scanner Fig 5.6 Image Thresholding using Previous Method**

In our work we have taken many MRI Scans images containing tumor region in them at various locations, each tumor has its own unique properties such as size, shape, volume, energy & brain.
The above figure shows the lack of proper segmentation in previous methods, due to the fact that tumor is a soft tissue and cannot by segmented by hard partitioning methods.



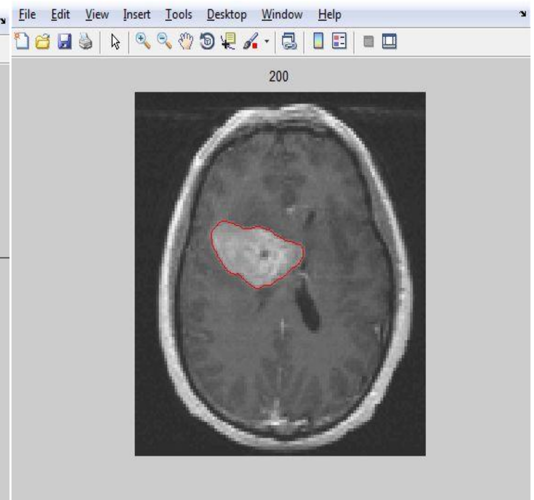




Fig 5.7 **Expert Region Selection in the proposed method Fig: 5.8 Final segmented Region using Fuzzy based Approach**

The Expert region is required to set the initial Seed region of the image as it allows the algorithm to search only in specified region of the image rather than the complete MRI Scan this makes algorithm faster.

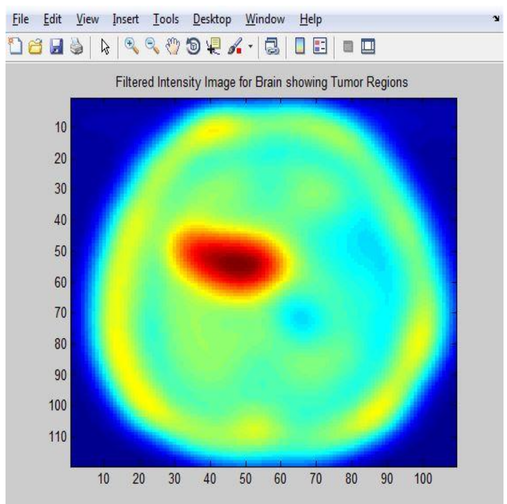



**Fig 5.10 Filtered Intensity Image for Brain showing Tumor Regions**

It is clearly shown in above figure that the Fuzzy based algorithm by utilizing the energy of the tumor in image quickly expands to the desired Region of interest that is Tumor taking at from 50 to at most 200 iterations in just a few seconds. Bar chart below describes the Number of iterations vs. Time required for each MRI image.-

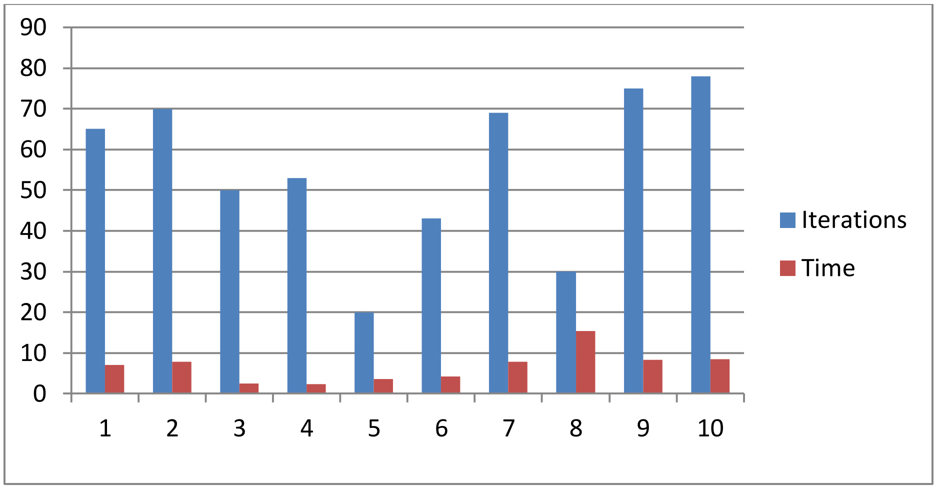



**Fig 5.10 Number of iterations vs Time required for each image**

Conclusion: Image segmentation is an important research area because it plays a fundamental role in image analysis, and understanding. Segmenting an image is the most challenging and difficult task because there exist different objects and a huge variations between them using a general framework. With the advent of modern publishing technologies, the layout of today's documents has never been more complex. Most of them contain not only text and background regions, but also graphics, tables and pictures. Therefore scanned documents must often be segmented before other document processing techniques, such as compression or rendering, can be applied. Traditional approaches to document segmentation, usually involve partitioning the document images into blocks, and then classifying each block

The results show that Fuzzy based Segmentation can successfully segment a tumor provided the parameters are set properly in MATLAB environment. Watershed Segmentation algorithm performance is better for the cases where the intensity level difference between the tumor and non tumor regions is higher. It can also segment non homogenous tumors providing the non homogeneity is within the tumor region. This proves that methods aimed at general purpose segmentation tools in medical imaging can be used for automatic segmentation of brain tumors.

The quality of the segmentation was similar to manual segmentation and will speed up segmentation in operative imaging. Among the segmentation methods investigated, the watershed segmentation is marked out best out of all others.

Future scope: The user interface in the main application must be extended to allow activation of the segmentation and to collect initialization points from a pointing device and transfer them to the segmentation module. Finally the main program must receive the segmented image and present the image as an opaque volume. It has only one limitation that the method is semi-automatic. Further work can be carried out to make this method automatic so that it can calculate the dimensions of the segmented tumor automatically.

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