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Image Segmentation Technology and its application in Digital Image Processing

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Abstract*- This paper deals with the implementation of Simple Algorithm for detection of range and shape of tumor in brain MR images. Tumor is an uncontrolled growth of tissues in any part of the body. Tumors are of different types and they have different Characteristics and different treatment. As it is known, brain tumor is inherently serious and life-threatening because of its character in the limited space of the intracranial cavity (space formed inside the skull). Most Research in developed countries show that the number of people who have brain tumors were died due to the fact of inaccurate detection. Generally, CT scan or MRI that is directed into intracranial cavity produces a complete image of brain. This image is visually examined by the physician for detection & diagnosis of brain tumor. However this method of detection resists the accurate determination of stage & size of tumor. To avoid that, this project uses computer aided method for segmentation (detection) of brain tumor based on the combination of two algorithms. This method allows the segmentation of tumor tissue with accuracy and reproducibility comparable to manual segmentation. In addition, it also reduces the time for analysis. At the end of the process the tumor is extracted from the MR image and its exact position and the shape also determined. The stage of the tumor is displayed based onthe amount of area calculated from the cluster.

I.INTRODUCTION

An image may be defined as a two-dimensional function, f(x, y), where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y, and the amplitude values of f are all finite, discrete quantities, we call the image a digital image. The field of digital image processing refers to processing digital images by means of a digital computer. Note that a digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are referred to as picture elements, image elements, pels, and pixels. Pixel is the term most widely used to denote the elements of a digital image.

Vision is the most advanced of our senses, so it is not surprising that images play the single most important role in human perception. However, unlike humans, who are limited to the visual band of the electromagnetic (EM) spectrum, imaging machines cover almost the entire EM spectrum, ranging from gamma to radio waves. They can operate on images generated by sources that humans are not accustomed to associating with images. These include ultra-sound, electron microscopy, and computer-generated images. Thus, digital image processing encompasses a wide and varied field of applications. There is no general agreement among authors regarding where image processing stops and other related areas, such as image analysis and computer vision, start. Sometimes a distinction is made by defining image processing as a discipline in which both the input and output of a process are images.

The field of AI is in its earliest stages of infancy in terms of development, with progress having been much slower than originally anticipated. The area of image analysis (also called image understanding) is in between image processing and computer vision. There are no clear-cut boundaries in the continuum from image processing at one end to computer vision at the other. However, one useful paradigm is to consider three types of computerized processes in this continuum: low-, mid-, and high-level processes. Low- level processes involve primitive operations such as image preprocessing to reduce noise, contrast enhancement, and image.Postscript, a standard vector format. Has numerous sub-standards and can be difficult to transport across platforms and operating systems.

They portray spatial information that we can recognize as objects. Human beings are good at deriving information from such images, because of our innate visual and mental abilities. About 75% of the information received by human is in pictorial form. An image is digitized to convert it to a form which can be stored in a computer's memory or on some form of storage media such as a hard disk or CD-ROM. This digitization procedure can be done by a scanner, or by a video camera connected to a frame grabber board in a computer. Once the image has been digitized, it can be operated upon by various image processing operations.

Image processing operations can be roughly divided into three major categories, Image Compression, Image Enhancement and Restoration, and Measurement Extraction. It involves reducing the amount of memory needed to store a digital image. Image defects which could be caused by the digitization process or by faults in the imaging set-up (for example, bad lighting) can be corrected using Image Enhancement techniques. Once the image is in good condition, the Measurement Extraction operations can be used to obtain useful information from the image. Some examples of Image Enhancement and Measurement Extraction are given below. The examples shown all operate on 256 grey-scale images. This means that each pixel in the image is stored as a number between 0 to 255, where 0 represents a black pixel, 255 represents a white pixel and values in-between represent shades of grey. These operations can be extended to operate on colour images. The examples below represent only a few of the many techniques available for operating on images. Details about the inner workings of the operations have not been given, but some references to books containing this information are given at the end for the interested reader. As we mentioned in the preface, human beings are predominantly visual creatures: we rely heavily on our vision to make sense of the world around us. We not only look at things to identify and classify them, but we can scan for differences, and obtain an overall rough feeling for a scene with a quick glance. Humans have evolved very precise visual skills: we can identify a face in an instant; we can differentiate colors; we can process a large amount of visual information very quickly.

However, the world is in constant motion: stare at something for long enough and it will change in some way. Even a large solid structure, like a building or a mountain, will change its appearance depending on the time of day (day or night); amount of sunlight (clear or cloudy), or various shadows falling upon it. We are concerned with single images: snapshots, if you like, of a visual scene. Although image processing can deal with changing scenes, we shall not discuss it in any detail in this text. For our purposes, an image is a single picture which represents something.It may be a picture of a person, of people or animals, or of an outdoor scene, or a microphotograph of an electronic component, or the result of medical imaging. Even if the picture is not immediately recognizable, it will not be just a random blur.

II. LITERATURE SURVEY

2.1 Topic: "Supervised and Unsupervised Segmentation"

Image segmentation objective is to segregate the image into mutually exclusive regions, which are similar with respect to pre-defined subsets. This objective can be accomplished using two methods of segmentation methods- Supervised and Unsupervised methods. The detailed explanations about these methods are as follows.

2.2 Unsupervised segmentation

If for training input vectors, target output is unknown, training method adopted is unsupervised learning. In the previous years, various unsupervised learning methods such as K-means and fuzzy clustering has gained popularity for brain tumor segmentation.The main aim of this type of segmentation is to segment the image into areas that have similar intensity and has well defined anatomic properties. Unsupervised segmentation of brain tumor achieve its anatomic goal by segmenting the image into atleast two anatomically regions, one is tumor and other is edema. The advantage of this type is that it can handle very difficult tasks such as brain tumor segmentation. It produces an accurate segmentation of different regions present in heterogeneous tumor. Disadvantages of this segmentation are: number of regions is to be known before, tumors may not be specified clearly. This disadvantage can be avoided using skull stripping. Skull stripping is a pre-processing step to wipe out noncerebral tissue such as fat, muscle, skin, skull which are not desired region of interest

2.3 Supervised segmentation

In supervised learning, the network is provided with series of sample inputs and output is compared with expected response. It involves both training phase that uses labelled data that maps features to labels and testing phase is used to map labels to unlabeled data. The advantage of this type is that training set can be changed; it can reduce the manual task by providing labelled data. Irrespective of its advantages, it suffers from disadvantages that it requires patient specific training for brain tumor supervised segmentation and also human variability is also a concern.

2.4 Topic: "Image segmentation via adaptive k-mean clustering and knowledge-based morphological operations"

Image segmentation remains one of the major challenges in image analysis. In medical applications, skilled operators are usually employed to extract the desired regions that may be anatomically separate but statistically indistinguishable. Such manual processing is subject to operator errors and biases, is extremely time consuming, and has poor reproducibility. We propose a robust algorithm for the segmentation of three-dimensional (3-d) image data based on a novel combination of adaptive k-mean clustering and knowledge-based morphological operations. The proposed adaptive k-mean clustering algorithm is capable of segmenting the regions of smoothly varying intensity distributions. Spatial constraints are incorporated in the clustering algorithm through the modeling of the regions by gibbs random fields. Knowledge-based morphological operations are then applied to the segmented regions to identify the desired regions according to the a priori anatomical knowledge of the region-of-interest. This proposed technique has been successfully applied to a sequence of cardiac ct volumetric images to generate the volumes of left ventricle chambers at 16 consecutive temporal frames. Our final segmentation results compare favorably with the results obtained using manual outlining. Extensions of this approach to other applications can be readily made when a priori knowledge of a given object is available.

2.5 Topic: "Medical image segmentation using k-means clustering and improved watershed algorithm"

The use of the conventional watershed algorithm for medical image analysis is widespread because of its advantages, such as always being able to produce a complete division of the image. However, its drawbacks include over-segmentation and sensitivity to false edges. We address the drawbacks of the conventional watershed algorithm when it is applied to medical images by using k-means clustering to produce a primary segmentation of the image before we apply our improved watershed segmentation algorithm to it. The k-means clustering is an unsupervised learning algorithm, while the improved watershed segmentation algorithm makes use of automated thresholding on the gradient magnitude map and post-segmentation merging on the initial partitions to reduce the number of false edges and over-segmentation. By comparing the number of partitions in the segmentation maps of 50 images, we showed that our proposed methodology produced segmentation maps which have 92% fewer partitions than the segmentation maps produced by the conventional watershed algorithm.

III. EXISTING METHODS

Image segmentation is one of the most important steps in image partitioning and their analyses. It can be used for various applications in computer vision and digital image processing. Many of the applications require highly accurate and computationally faster image processing algorithms. The success of any application depends on reliability and accuracy of the image processing used. In this chapter, we have studied, reviewed and analyzed important threshold and region based image segmentation techniques and their variations.

Image acquisition digitizes the image captured by camera. Image enhancement is the process of manipulating an image so that the results are more suitable for specific applications. Image restoration improves an appearance of an image which tends to probabilities model of image degradation Morphological processes are the tools of extracting image components that are useful in the description and presentation of an image.Image segmentation approaches are commonly based on one of two fundamental properties of intensity values. In discontinuity based technique image is partitioned by sudden changes in intensity values whereas similarity based technique partitions an image by grouping together connected pixels in the region which fulfills predefined resemblance criteria. Boundary detection is equivalent to splitting one region into two, hence similarity based and discontinuity based techniques mirror each other. Segmentation methods based on these approaches are discussed in this section.

3.1 Image Segmentation Techniques

There are various image segmentation techniques.Some of them are:

i. Thresholding based segmentation
ii. Region based segmentation
iii. Watershed segmentation

3.2 Threshold Based Segmentation

Thresholding is one of the simplest approaches for image segmentation based on intensity levels. Threshold based technique works on the assumption that the pixels falling in certain range of intensity values represents one class and remaining pixels in the image represents the other class. Thresholding can be implemented either locally or globally. For global thresholding brightness threshold value is to be selected to segment the image into object and background. It generates binary image from given input image. The pixels satisfying threshold test are considered as object pixels with binary value '1' and other pixels are treated as background pixels with binary value '0'.

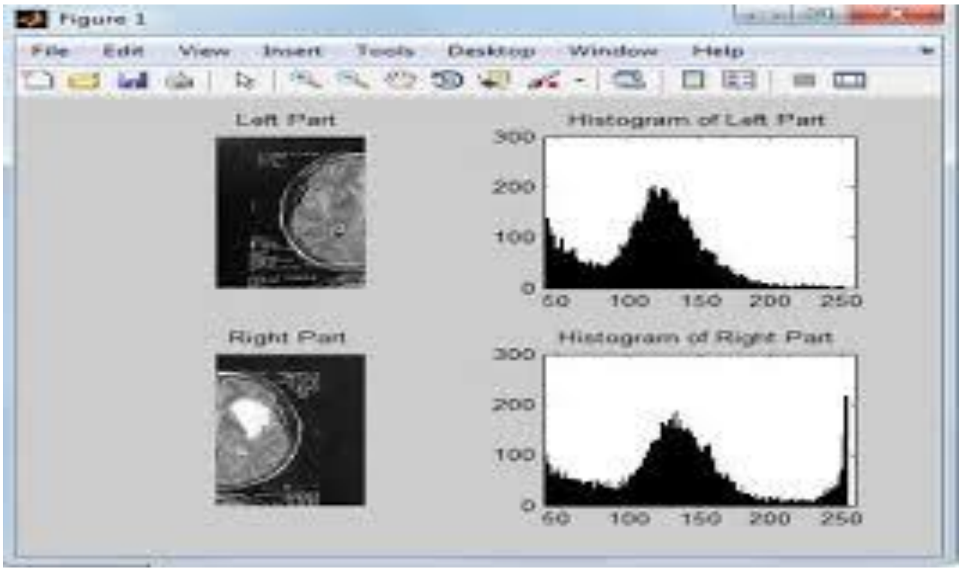

Fig 3.2Separation of image and histogram of two sides

Human brain is symmetrical about left and right side.Divide the brain into two equal halves as shown in Fig 3.2.Plot the histogram and compare them.If the histogram of left part and right part are equal no tumor present in the brain image.If the histogram of left part and right part are not equal then we can conclude that tumor is present in the brain..

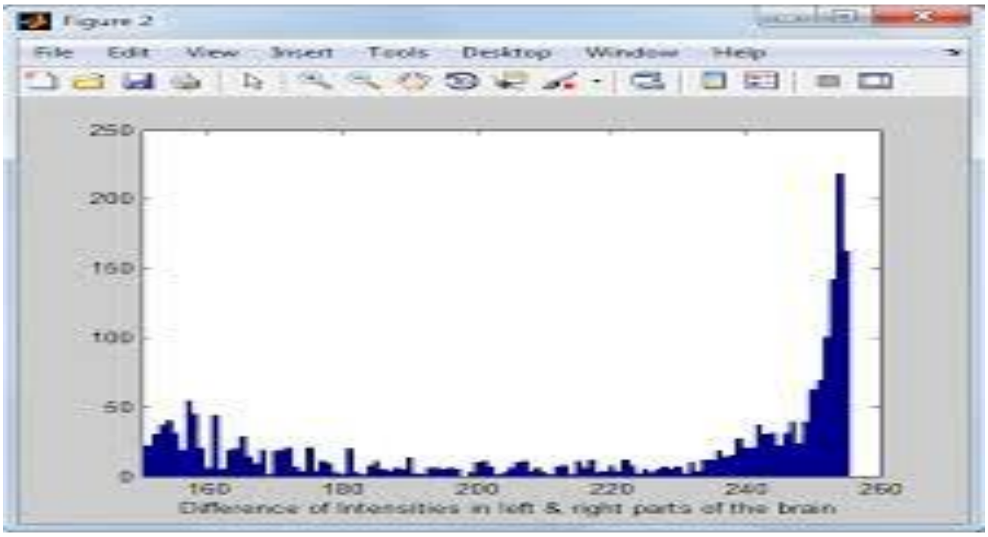

Fig3.3Difference in the intensity of the two side brain

The difference in the intensity of thetwo side brain is as shown in Fig3.3. According to Fig 3.3 a threshold point is set. The pixels that have intensity values below the threshold point are assigned to black colour and the pixels that have intensity values above threshold point are assigned to white color. The tumor has high intensity values and it appears in white color.

3.3 Drawbacks of Thresholding

- For an image with broad and flat valleys or without any peak, it doesn't works well.
- Neglects spatial information of an image, cannot guarantee that the segmented regions are contiguous.
- Highly noise sensitive.
- Selection of threshold is crucial, wrong choice may result into over or under segmentation.

IV. PROPOSED METHOD

4.1 Clustering:

Clustering is a method of grouping data objects into different groups, such that similar data objects belong to the same group and dissimilar data objects to different clusters. Current research increasing interest in digital image searching, classification, identification, management and storage. Some common but important applications of are person identification in movie clips and festive home videos, recognition in biometric system, natural scene classification for robot vision.The image clustering, an important technology for image processing, has been actively researched for a long period of time and explosive growth of the Web. Clustering approach is widely used in biomedical image segmentation and it is application are used for brain tumor detection as the normal and abnormal to find out the tumor on the brain.

Many different segmentation techniques are used in the image mining and image segmentation approaches can be divided into many parts as:

1. Clustering
2. Edge detection
3. Thresholding
4. Region extraction.

In this project, we discuss above the clustering concept in the image mining on the image segmentation process of the clustering and each object can be have its place of more than one clusters to be provisional upon the degree of relationship association on it.

Segmentation is an important process in most medical image analysis and classification for radio logical evaluation or computer-aided diagnosis.Basically,image segmentation methods can be classified into three categories:

1)Edge-based methods
2)Region-basedmethods
3)Pixel-based methods

k-means clustering is a key technique in pixel-based methods. Because pixel-based methods based on k-means clustering are simple and the computational complexity is relatively low compared with the region-based or edge-based methods, the application is more practicable. Furthermore means clustering is suitable for biomedical image segmentation as the number of clusters is usually known for images of particular regions of the human anatomy. Many researchers have proposed related research into k-means clustering segmentation. The improvements achieved by researchers have been remarkable.

4.2 Image Classification.

Two major categories of image classification techniques include

1. Unsupervised (calculated by software)
2. Supervised (human guided)

Unsupervised classification is where the outcomes (groupings of pixels with common characteristics) are based on the software analysis of an image without the user providing sample classes. The computer uses techniques to determine which pixels are related and groups them into classes. The user can specify which algorism the software will use and the desired number of output classes but otherwise does not aid in the classification process. However, the user must have knowledge of the area being classified when the groupings of pixels with common characteristics produced by the computer have to be related to actual features on the ground (such as wetlands, developed areas, coniferous forests, etc.).

Supervised classification is based on the idea that a user can select sample pixels in an image that are representative of specific classes and then direct the image processing software to use these training sites as references for the classification of all other pixels in the image. Training sites (also known as testing sets or input classes) are selected based on the knowledge of the user. The user also sets the bounds for how similar other pixels must be to group them together. These bounds are often set based on the spectral characteristics of the training area, plus or minus a certain increment (often based on "brightness" or strength of reflection in specific spectral bands). The user also designates the number of classes that the image is classified into. Many analysts use a combination of supervised and unsupervised classification processes to develop final output analysis and classified maps.

4.3 K-Mean Clustering

It is one of the techniques for the clustering concept in the data mining process and is very famous algorithm for the K-means clustering, because it is similar or simpler and easier in computation of an efficient K-means clustering algorithm.It is the simplest unsupervised learning algorithms that solve the well known clustering problems.K-means algorithm is an unsupervised clustering algorithm that classified in the input data points into multiple classes based on their intrinsic distance from other dataset points of his cluster

K-means clustering is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. K-means clustering aims to patition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in a partitioning of the data space.K-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early groupage is done. At this point we need to re-calculate k new centroids as centers of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the k centroids change their location step by step until no more changes are done.

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Finally, this algorithm aims at minimizing an objective function, in this case a squared error function. The objective function is given by

$$J(V) = \sum_{i=1}^{c}\sum_{j=1}^{c_i}\left\|x_i - v_j\right\|^2 \qquad (4.1)$$

ALGORITHM:

1.Give the no of cluster value as k.

2. Randomly choose the k cluster centers.
3. Calculate mean or center of the cluster.
4. Calculate the distance between each pixel to each cluster center.
5. If the distance is near to the center then move to that cluster.
6. Otherwise move to next cluster.
7. Re-estimate the center
8. Repeat the process until the center doesn't move.

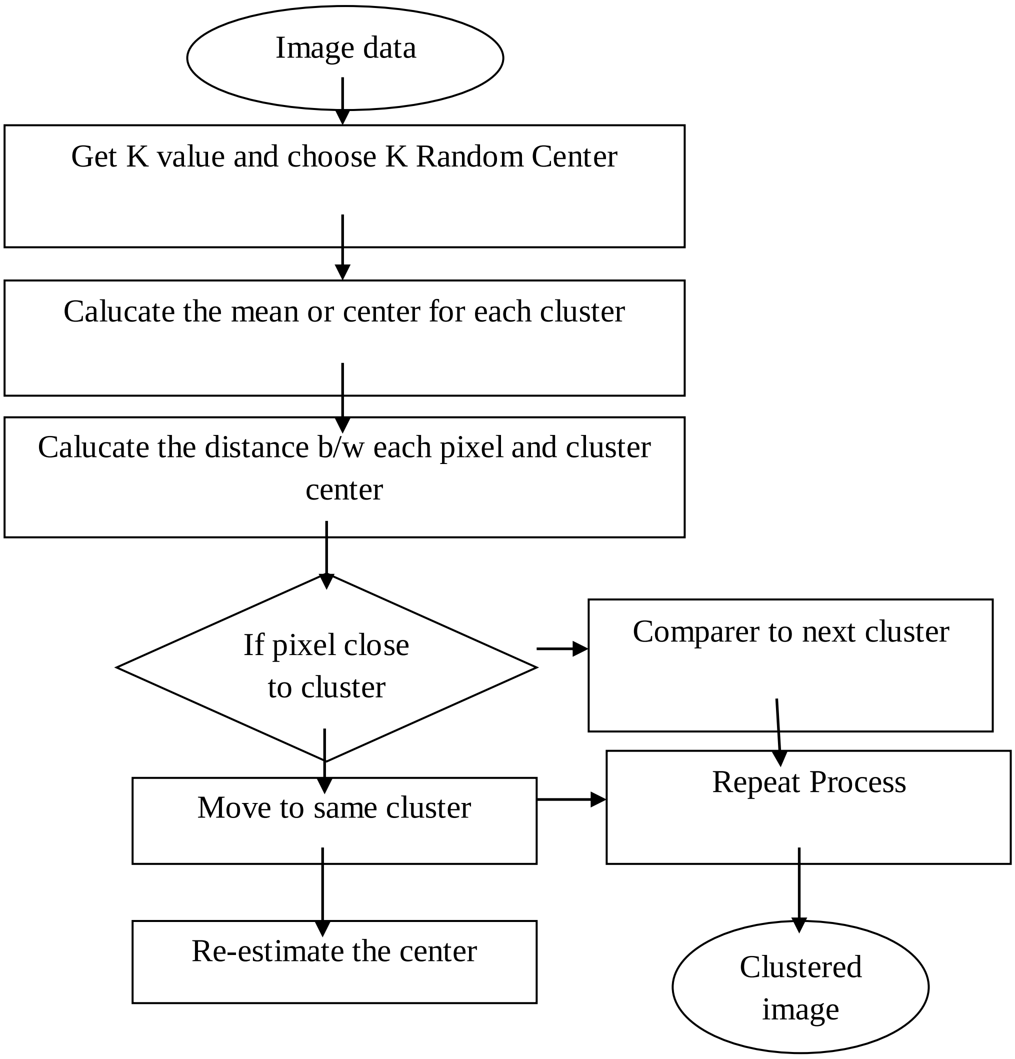

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Fig 4.2Flowchart for k-means Clustering

Fig 4.2 represents the diagrammatic representation of K-mean clustering algorithm

4.5 Strengths and Weaknesses

K-means is simple and can be used for a variety of data types. It is also a quite efficient, even though multiple runs are often performed. Some variants including bisecting K-means, are even more efficient, and are less susceptible to initialization problems. K-means is not suitable for all types of data, however. It cannot handle non-globular clusters or clusters of different sizes and densities, although it can typically find pure sub clusters if a large enough contains outlier. Outlier detection and removal can help significantly in such situations. Finally, K-means is restricted to data for which there is a notion of a center (centroid).

V. RESULTS

5.1 K-MEAN RESULTS:

Consider the brain MR image with tumor and edema shown in Fig 5.1 as an input image. The image is a gray level image of size 144x144 and of bmp format.

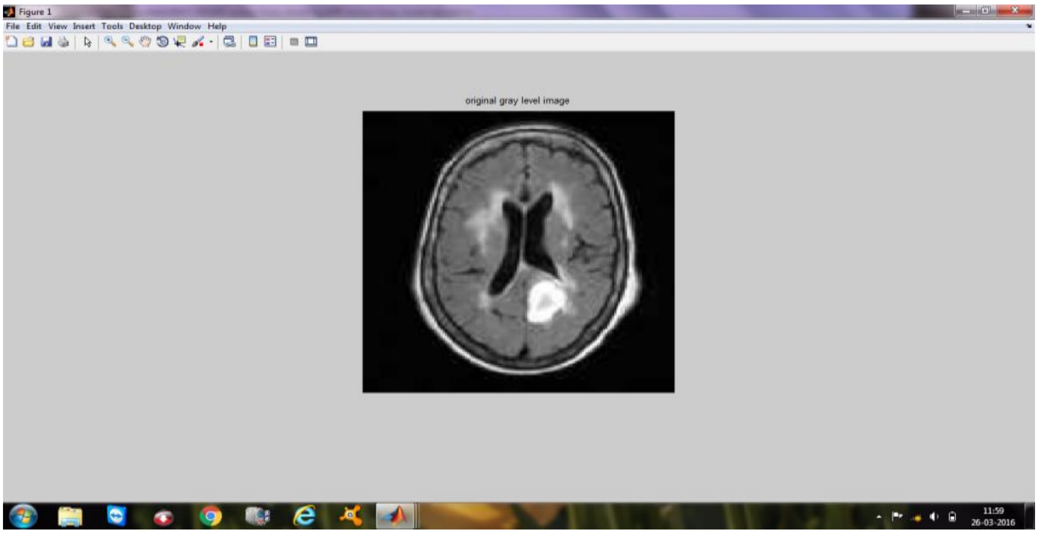

Fig 5.1 Original gray level image

Original gray level image is converted to pseudo image as shown in Fig 5.2 by using jet command. The output image obtained after applying jet command is a color image having size 144x144 and of bmp format.

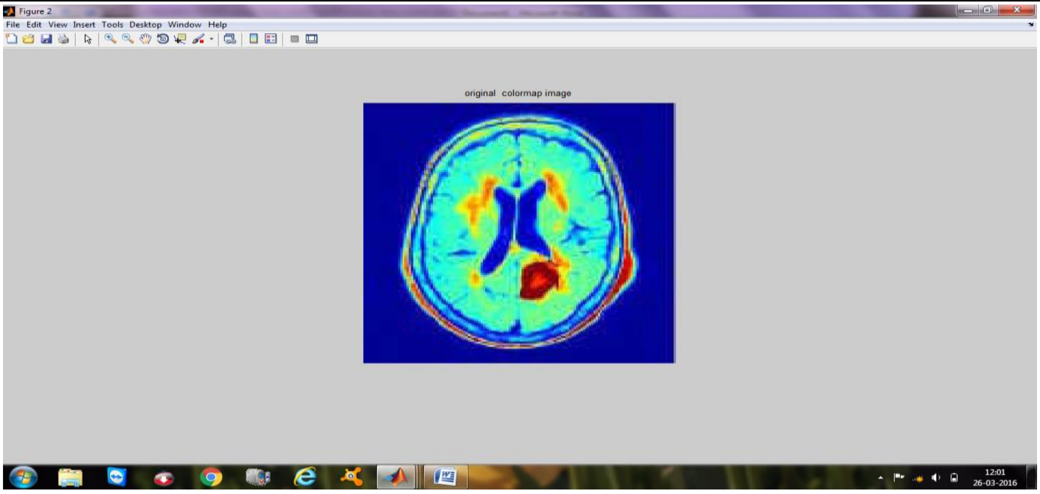

Fig 5.2 Original colormap image

The pseudo image is converted into color space translated image as shown in Fig 5.3 by using L,a,b true color tone correction.The output image now obtained is a color image of size 144x144 and of bmp format.

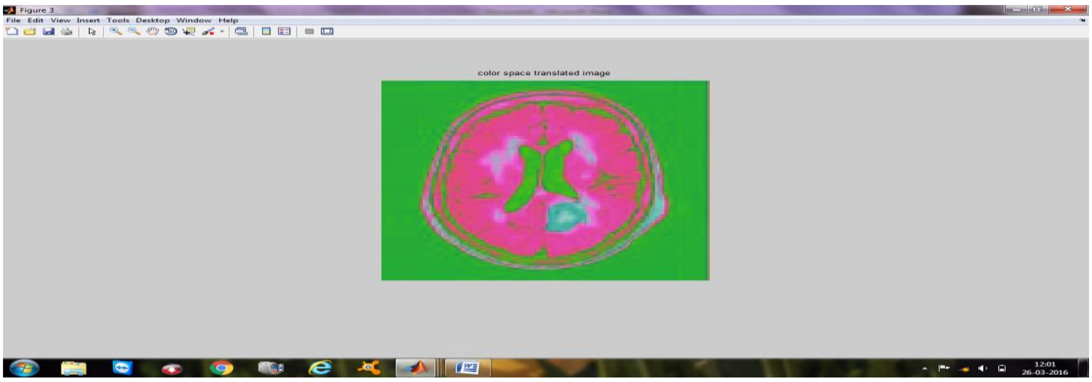

Fig 5.3 Color space translated image

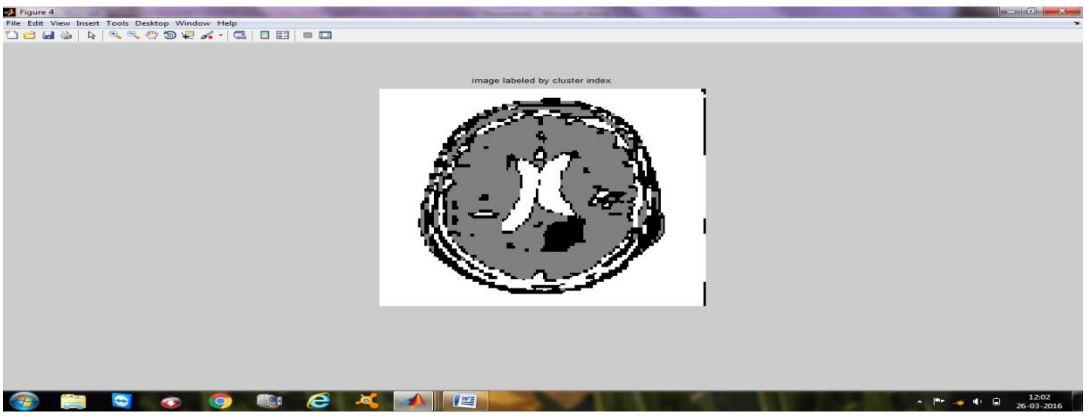

Fig 5.4 Image labelled by cluster index

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Image representation of the first cluster image is represented as shown in Fig 5.5 and it also represents both tumor and edema areas with blue and red color spaces.

Fig 5.5 Objects in cluster 1

Image representation of the second cluster image is represented as shown in Fig 5.6 and it also represents the non tumor area in brain.

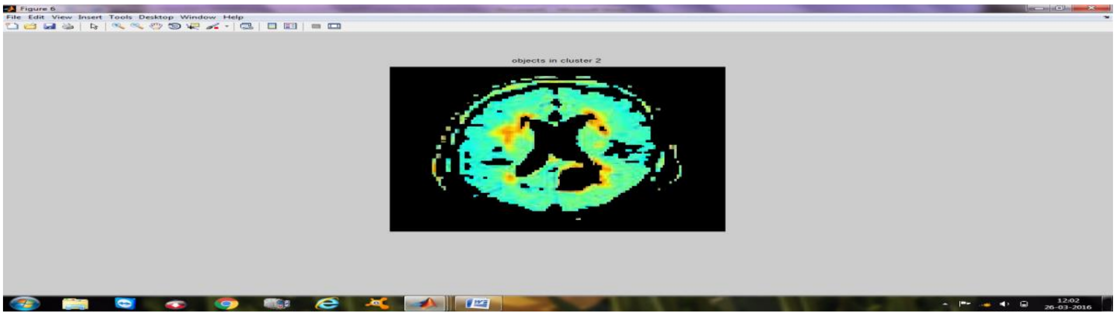

Fig 5.6 Objects in cluster 2

Image representation of the third cluster image is represented as shown in Fig 5.7 and it shows the celebral spinal fluid(CSF) in the brain.

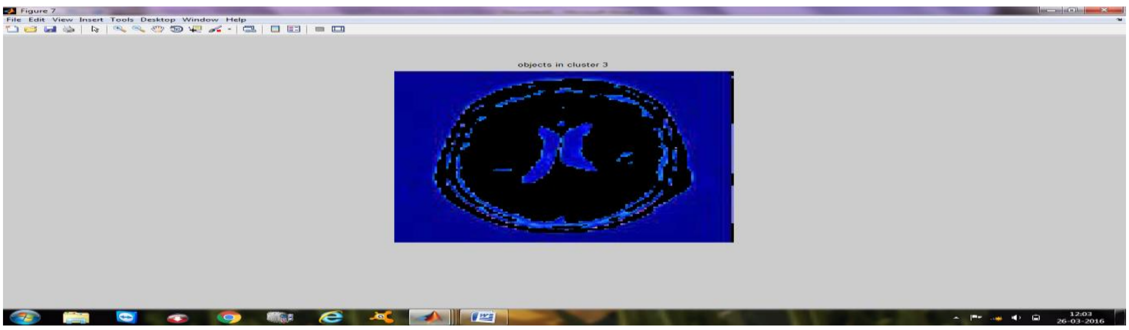

Fig 5.7 Objects in cluster 3

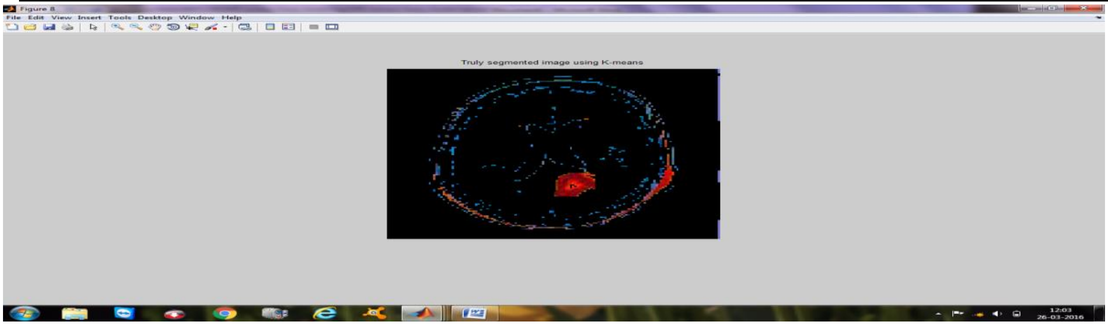

Fig 5.8 Truly segmented image using k-means

VI. CONCLUSION

There are different types of tumors are available. They may be as mass in brain or malignant over the brain.Suppose if it is a mass then K- means algorithm is enough to extract it from the brain cells. If there is any noise are present in the MR image it is removed before the K-means process. The noise free image is given as a input to the k-means and tumor is extracted from the MRI image. And then segmentation using Fuzzy C means for accurate tumor shape extraction of malignant tumor and thresholding of output in feature extraction. Finally approximate reasoning for calculating tumor shape and position calculation. The experimental results are compared with other algorithms. The proposed method gives more accurate result. In future 3D assessment of brain using 3D slicers with MATLAB can be developed.

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