ABSTRACT

This project 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 on the amount of area calculated from the cluster.

CHAPTER 1
INTRODUCTION

1.1 Image Processing

Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image. Nowadays, image processing is among rapidly growing technologies. It forms core research area within engineering and computer science disciplines too.

Image processing basically includes the following three steps:

- Importing the image via image acquisition tools.
- Analysing and manipulating the image.
- Output in which result can be altered image or report that is based on image analysis.

There are two types of methods used for image processing namely, analog and digital image processing. Analog image processing can be used for the hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques. Digital image processing techniques help in manipulation of the digital images by using computers. The three general phases that all types of data have to undergo while using digital technique are pre-processing, enhancement, and display, information extraction.

1.2 Fundamentals of Image Processing

- **Image Acquisition**

This is the first step or process of the fundamental steps of digital image processing. Image acquisition could be as simple as being given an image that is already in digital form. Generally, the image acquisition stage involves preprocessing such as contrast enhancement, noise removal etc.

- **Image Enhancement**

Image enhancement is among the simplest and most appealing areas of digital image processing. Basically, the idea behind enhancement techniques is to bring out detail that is obscured, or simply to highlight certain features of interest in an image such as changing brightness & contrast etc.

- **Image Restoration**

Image restoration is an area that also deals with improving the appearance of an image. However, unlike enhancement, which is subjective, image restoration is objective.The restoration techniques tend to be based on mathematical or probabilistic models of image degradation.

- **Color Image Processing**

Color image processing is an area that has been gaining its importance because of the significant increase in the use of digital images over the Internet. This may include color modelling and processing in a digital domain etc.

- **Wavelets and Multiresolution Processing**

Wavelets are the foundation for representing images in various degrees of resolution.Images subdivision successively into smaller regions for data compression and for pyramidal representation.

- **Compression**

Compression deals with techniques for reducing the storage required to save an image or the bandwidth to transmit it. Particularly in the uses of internet it is very much necessary to compress data.

- **Morphological Processing**

Morphological processing deals with tools for extracting image components that are useful in the representation and description of shape.

- **Segmentation**

Segmentation procedures partition an image into its constituent parts or objects. In general, autonomous segmentation is one of the most difficult tasks in digital image processing.

1.3 Biomedical Image Processing

Biomedical image processing has experienced dramatic expansion, and has been an interdisciplinary research field attracting expertise from applied mathematics, computer sciences, engineering, physics, biology and medicine. Computer-aided diagnostic processing has already become an important part of clinical routine. Accompanied by a rush of new development of high technology and use of various imaging modalities, more challenges arise. For example, how to process and analyze a significant volume of images so that high quality information can be produced for disease diagnoses and treatment. The principal objectives of this course are to provide an introduction to basic concepts and techniques for medical image processing and to promote interests for further study and research in medical imaging processing.

Imaging is an essential aspect of medical science to visualize the structures of the human body. Several new complex medical imaging modalities such as x-ray, Magnetic Resonance Imaging (MRI) and ultra sound,Computerized Tomography(CT) strongly depend on computer technology to generate or display digital images. With computer techniques, multidimensional digital images of physiological structures can be processed and manipulated to help visualize hidden diagnostic features that are otherwise difficult or impossible to identify using planar imaging methods.

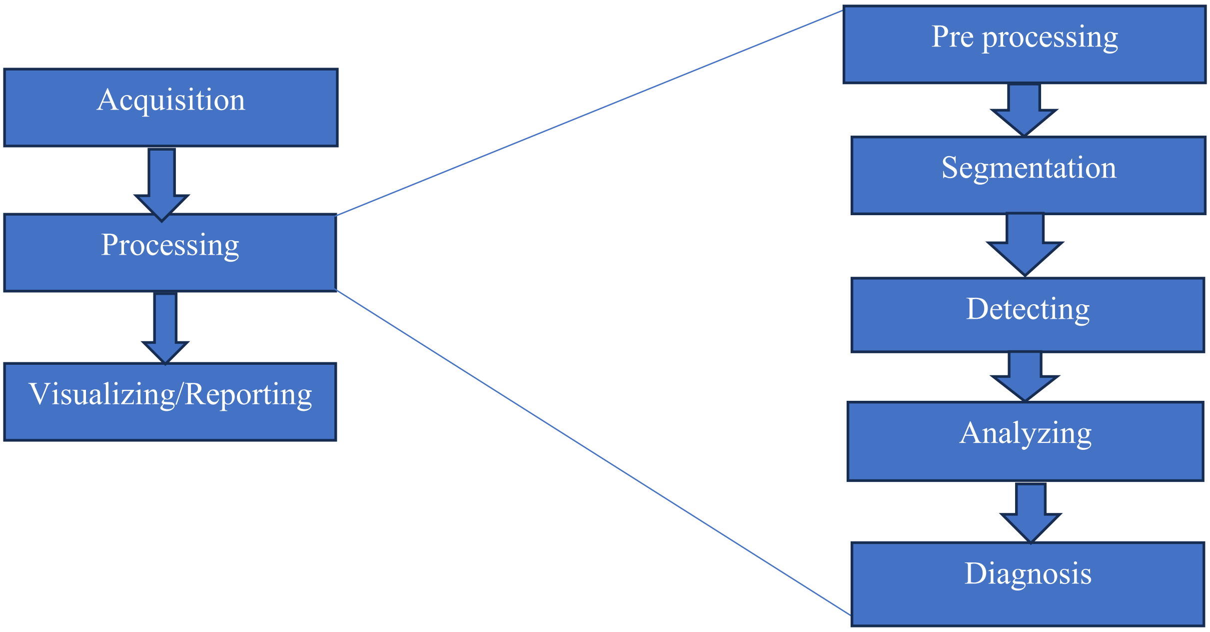


Fig1.1 Basic Block Diagram Of Image Processing

Fig 1.1 shows the basic steps involved in image processing. Acquisition means capturing the input image by means of MRI,CT etc. Procesing involves many steps like pre processing, segmentation, detecting, analysis and diagnosis. Pre processing is nothing but removing the noise from the input image by using filters.

1.4 Neurological Disorders

Brain tumor segmentation is one of the crucial procedures in surgical and treatment planning. However, at present, brain tumor segmentation in brain tumor images is mostly performed manually in clinical practice. Apart from being time consuming, manual brain tumor delineation is difficult and depends on the individual operator. Currently, multimodal MRI images are used simultaneously by radiologists in segmenting brain tumor images because multimodal MRI images can provide various data on tumors. In glioma, the tumor area is usually divided into necrosis, contrast-enhancing tumor, non-enhancing tumor, and edema. Different MRI image
modalities can reveal different parts in the tumor area.

Although multimodal MRI images can provide complementary information in the tumor area, brain tumor segmentation is still a challenging and difficult task. Brain tumors can have various sizes and shapes and may appear at different locations. Additionally, noise in brain tumor images increase the difficulty when segmenting tumors. Thus, designing of a semi-automatic or automatic brain tumor segmentation approach is necessary to provide an acceptable performance. Numerous algorithms have been developed to perform brain tumor detection and segmentation. These methods include thresholding and morphological techniques, watershed method, region growing approach, supervised and unsupervised methods.

1.5 Brain Tumors

Under certain conditions, brain cells grow and multiply uncontrollably because for some reasons, the mechanism that control normal cells is unable to regulate the growth of the brain cells. The abnormal mass of brain tissue is the brain tumor that occupies space in the skull and interrupts the normal functions of brain and creates an increasing pressure in the brain. Due to increased pressure on the brain, some brain tissues are shifted, pushed against the skull are responsible for the damage of the nerves of the other healthy brain tissues.

A tumor may be primary or secondary. If it is the origin, then it is known as primary. If the part of the tumor spreads to another place and grows on its own, then it is known as secondary. The brain tumor affects CSF (Cerebral Spinal Fluid) and causes strokes. The physician gives the treatment for the strokes rather than the treatment for tumors. So the detection of the tumor is important for that treatment. The life expectancy of the person affected by the brain tumor will increase if it is detected at an earlier stage. The detection of the malignant tumor is somewhat difficult to mass tumor.

CHAPTER 2

IMAGE PROCESSING

2.1 Digital Image Processing :

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.

We believe this to be a limiting and somewhat artificial boundary. For example, under this definition, even the trivial task of computing the average intensity of an image (which yields a single number) would not be considered an image processing operation. On the other hand, there are fields such as computer vision whose ultimate goal is to use computers to emulate human vision, including learning and being able to make inferences and take actions based on visual inputs. This area itself is a branch of artificial intelligence (AI) whose objective is to emulate human intelligence.

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.

2.2 Definition of Image:

An image is an array, or a matrix, of square pixels (picture elements) arranged in columns and rows.

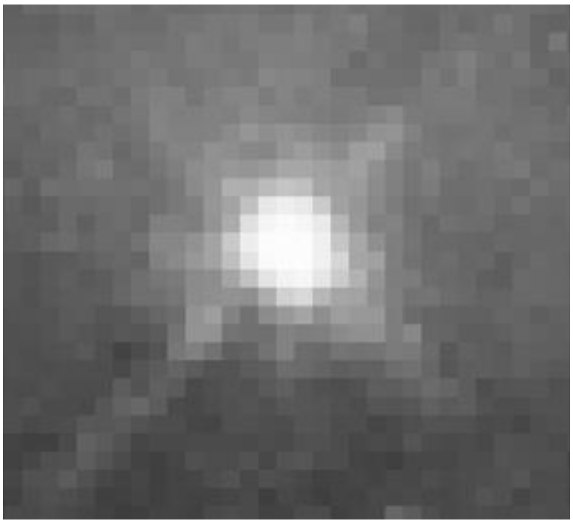


Fig2.1: An array or a matrix of pixels arranged in columns and rows

In a (8-bit) greyscale image each picture element has an assigned intensity that ranges from 0 to 255. A grey scale image is what people normally call a black and white image, but the name emphasizes that such an image will also include many shades of grey.

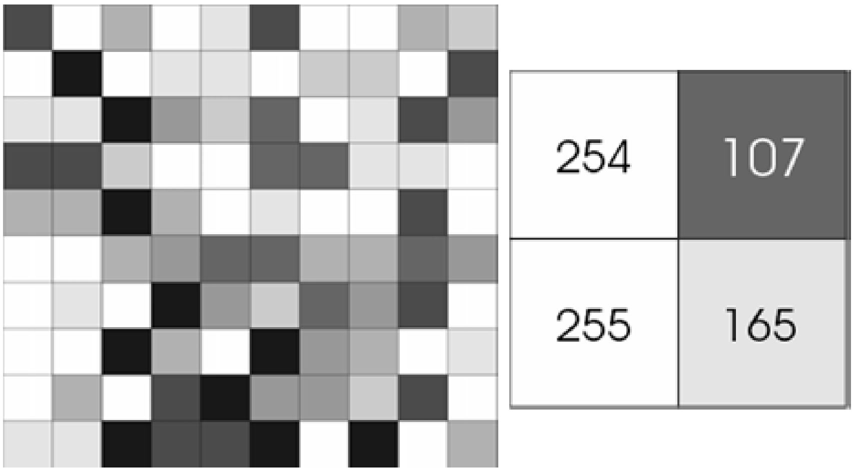


Fig2.2: 8 bit = 256 tones or grayscales image

In Figure 2.2 Each pixel has a value from 0 (black) to 255 (white). The possible range of the pixel values depend on the color depth of the image, here 8 bit = 256 tones or grayscales. A normal grayscale image has 8 bit colour depth = 256 grayscales. A "true colour" image has 24 bit colour depth = 8 x 8 x 8 bits = 256 x 256 x 256 colours = ~16 million colours.

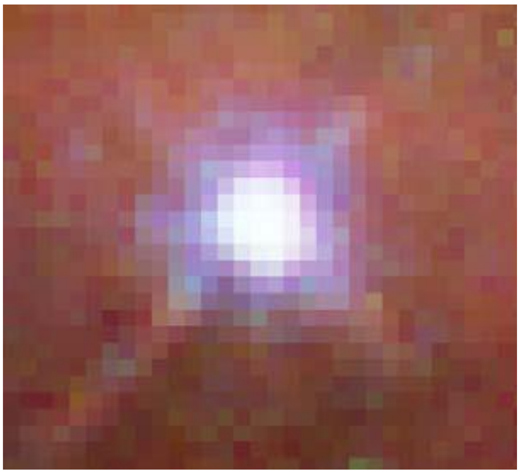


Fig2.3: A true-color image assembled from three grayscale images

Figure 2.3 shows A true-color image assembled from three grayscale images colored red, green and blue. Such an image may contain up to 16 million different colors. Some grayscale images have more grayscales, for instance 16 bit = 65536 grayscales. In principle three grayscale images can be combined to form an image with 281,474,976,710,656 grayscales.

There are two general groups of ‘images’: vector graphics (or line art) and bitmaps (pixel-based or ‘images’).

Some of the most common file formats:

GIF:

An 8-bit (256 color), non-destructively compressed bitmap format. Mostly used for web. Have several sub-standards one of which is the animated GIF.

JPEG:

A very efficient (i.e. much information per byte) destructively compressed 24 bit (16 million colours) bitmap format. Widely used, especially for web and Internet (bandwidth-limited).

TIFF:

The standard 24 bit publication bitmap format.Compresses non-destructively with, for instance, Lempel-Ziv-Welch (LZW) compression.

PS:

Postscript, a standard vector format. Has numerous sub-standards and can be difficult to transport across platforms and operating systems.

Pictures are the most common and convenient means of conveying or transmitting information. A picture is worth a thousand words. Pictures concisely convey information about positions, sizes and inter relationships between objects.

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.

2.3 Images and Pictures:

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.

Image processing involves changing the nature of an image in order to either

1. Improve its pictorial information for human interpretation,
2. Render it more suitable for autonomous machine perception.

We shall be concerned with digital image processing, which involves using a computer to change the nature of a digital image. It is necessary to realize that these two aspects represent two separate but equally important aspects of image processing. A procedure which satisfies condition, a procedure which makes an image look better may be the very worst procedure for satisfying condition. Humans like their images to be sharp, clear and detailed; machines prefer their images to be simple and uncluttered.

2.4 Images and Digital Images:

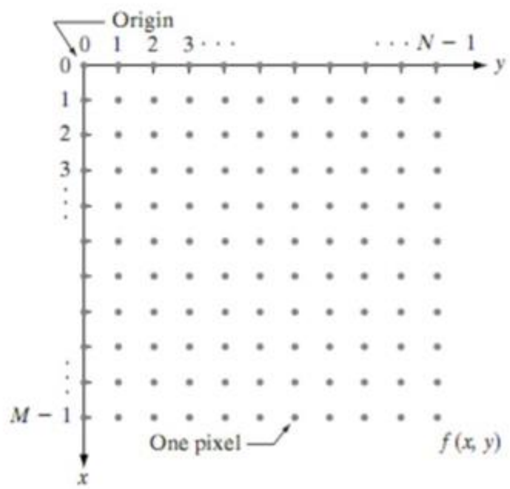


Fig2.4: Coordinate convention used to represent digital mage

Suppose we take an image, a photo, say. For the moment, lets make things easy and suppose the photo is black and white (that is, lots of shades of grey), so no color. We may consider this image as being a two dimensional function, where the function values give the brightness of the image at any given point.

We may assume that in such an image brightness values can be any real numbers in the range (black) (white).A digital image can be considered as a large array of discrete dots, each of which has a brightness associated with it. These dots are called picture elements, or more simply pixels. The pixels surrounding a given pixel constitute its neighborhood. A neighborhood can be characterized by its shape in the same way as a matrix: we can speak of a neighborhood,. Except in very special circumstances, neighborhoods have odd numbers of rows and columns; this ensures that the current pixel is in the centre of the neighborhood.

2.5 Fundamental Steps in Digital Image Processing:

Image acquisition is the first process shown in Fig.2. Note that acquisition could be as simple as being given an image that is already in digital form. Generally, the image acquisition stage involves preprocessing, such as scaling. Image enhancement is among the simplest and most appealing areas of digital image processing.

Basically, the idea behind enhancement techniques is to bring out detail that is obscured, or simply to highlight certain features of interest in an image. A familiar example of enhancement is when we increase the contrast of an image because “it looks better.” It is important to keep in mind that enhancement is a very subjective area of image processing. Image restoration is an area that also deals with improving the appearance of an image. However, unlike enhancement, which is subjective, image restoration is objective, in the sense that restoration techniques tend to be based on mathematical or probabilistic models of image degradation.

Enhancement, on the other hand, is based on human subjective preferences regarding what constitutes a “good” enhancement result. Color image processing is an area that has been gaining in importance because of the significant increase in the use of digital images over the Internet.

The pixels surrounding a given pixel constitute its neighborhood. A neighborhood can be characterized by its shape in the same way as a matrix: we can speak of a neighborhood. Except in very special circumstances, neighborhoods have odd numbers of rows and columns; this ensures that the current pixel is in the centre of the neighborhood. Generally, the image acquisition stage involves preprocessing, such as scaling. Image enhancement is among the simplest and most appealing areas of digital image processing. We may assume that in such an image brightness values can be any real numbers in the range (black) (white).A digital image can be considered as a large array of discrete dots, each of which has a brightness associated with it.

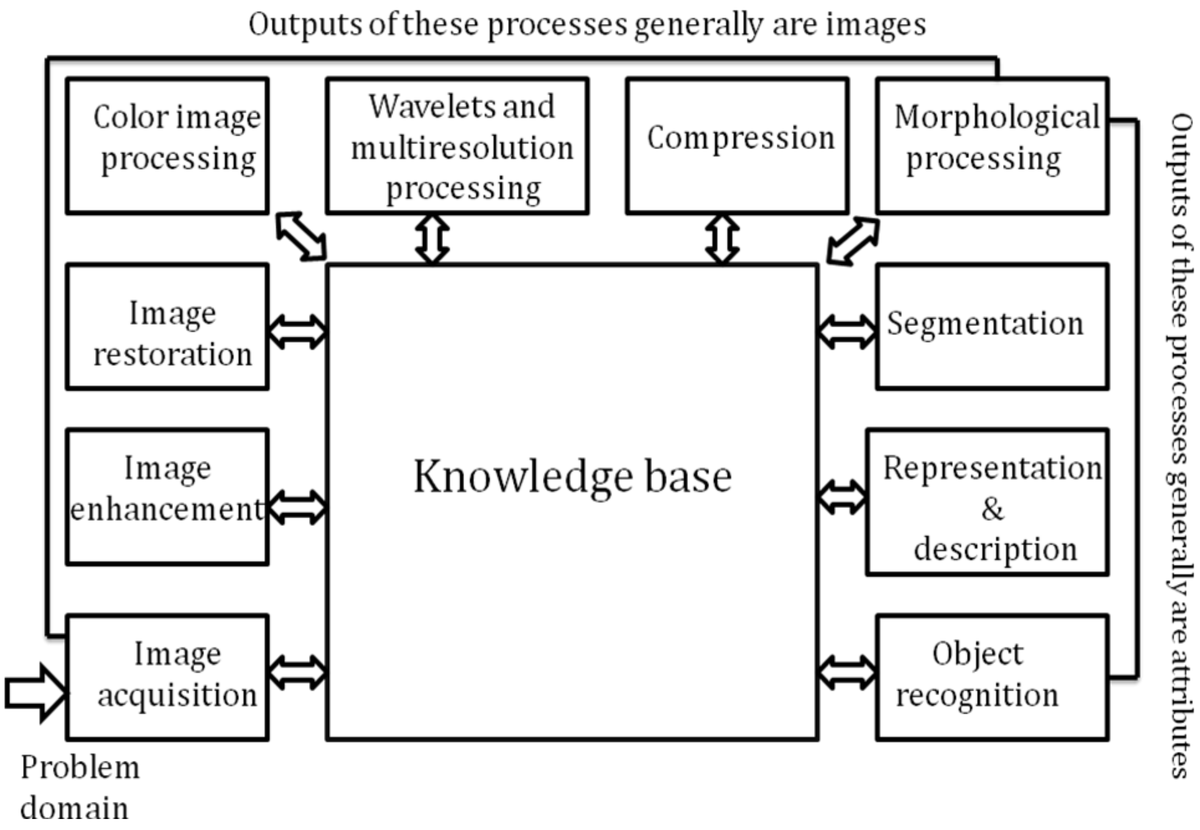


Fig2.5: Fundamental steps in Digital Image Processing

Wavelets are the foundation for representing images in various degrees of resolution. Compression, as the name implies, deals with techniques for reducing the storage required to save an image, or the bandwidth required to transmit it. Although storage technology has improved significantly over the past decade, the same cannot be said for transmission capacity. This is true particularly in uses of the Internet, which are characterized by significant pictorial content. Image compression is familiar (perhapsinadvertently) to most users of computers in the form of image file extensions, such as the jpg file extension used in the JPEG (Joint Photographic Experts Group) image compression standard.

Morphological processing deals with tools for extracting image components that are useful in the representation and description of shape. Segmentation procedures partition an image into its constituent parts or objects. In general, autonomous segmentation is one of the most difficult tasks in digital image processing. A rugged segmentation procedure brings the process a long way toward successful solution of imaging problems that require objects to be identified individually. On the other hand, weak or erratic segmentation algorithms almost always guarantee eventual failure.

Representation and description almost always follow the output of a segmentation stage, which usually is raw pixel data, constituting either the boundary of a region (i.e., the set of pixels separating one image region from another) or all the points in the region itself. In either case, converting the data to a form suitable for computer processing is necessary. The first decision that must be made is whether the data should be represented as a boundary or as a complete region. Boundary representation is appropriate when the focus is on external shape characteristics, such as corners and inflections. Regional representation is appropriate when the focus is on internal properties, such as texture or skeletal shape. In some applications, these representations complement each other. Choosing a representation is only part of the solution for transforming raw data into a form suitable for subsequent computer processing.

A method must also be specified for describing the data so that features of interest are highlighted. Description, also called feature selection, deals with extracting attributes that result in some quantitative information of interest or are basic for differentiating one class of objects from another. Recognition is the process that assigns a label (e.g., "vehicle") to an object based on its descriptors. We conclude our coverage of digital image processing with the development of methods for recognition of individual objects.

2.6 Applications and Usage:

Since digital image processing has very wide applications and almost all of the technical fields are impacted by DIP, we will just discuss some of the major applications of DIP. Digital Image processing is not just limited to adjust the spatial resolution of the everyday images captured by the camera. It is not just limited to increase the brightness of the photo, e.t.c. Rather it is far more than that. Electromagnetic waves can be thought of as stream of particles, where each particle is moving with the speed of light. Each particle contains a bundle of energy. This bundle of energy is called a photon. The electromagnetic spectrum according to the energy of photon is shown below. In this electromagnetic spectrum, we are only able to see the visible spectrum.

CHAPTER 3
LITERATURE SURVEY

Topic: “Manual and Automated tumor segmentation”

The classification of Brain tumor segmentation methods can be made depending on the degree of human interaction.

Topic: “Manual segmentation”

It involves delineation of the boundaries of tumor manually and representing region of anatomic structures with various labels Manual segmentation requires software tools for the ease of drawing regions of interest (ROI), is a tedious and exhausting task.MRI scanners produce multiple 2-D slices and the human expert has to mark tumor regions carefully, otherwise it will generate jaggy images that lead to poor segmentation results.

Topic: “Semi-automatic segmentation”

In semi-automatic brain tumor segmentation, human interaction is least as possible. The semiautomatic or interactive brain tumor segmentation components consist of computational part, interactive part and the user interface. Since it involves both computer and human’s expertise, result depends on both the combination. Efficient segmentation of brain tumor is possible through this strategy but it is also subjected to variations between expert users and within same user.

Topic: “Fully automatic segmentation”

In this method, there is no intervention of human and segmentation of tumor is determined with the help of computer. It involves the human intelligence and is developed with soft computing techniques, which is a difficult task. Brain tumor segmentation has various properties which reduce the advantage of humans over machines. These methods are likely to be used for large batch of images in research environment. However; these methods have not gained popularity for clinical practice, due to lack of transparency and interpretability.

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.

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 non cerebral tissue such as fat, muscle, skin, skull which are not desired region of interest

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.

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.

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.

Topic: "A fast parallel using clustering algorithm for large spatial databases"

The clustering algorithm DBSCAN relies on a density-based notion of clusters and is designed to discover clusters of arbitrary shape as well as to distinguish noise. In this paper, we present PDBSCAN, a parallel version of this algorithm. We use the 'shared-nothing' architecture with multiple computers interconnected through a network. A fundamental component of a shared-nothing system is its distributed data structure. We introduce the dR*-tree, a distributed spatial index structure in which the data is spread among multiple computers and the indexes of the data are replicated on every computer.

EXISTING METHODS

3.1 Image segmentation

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 is the most difficult ask in digital image processing which separates objects from the background. Representation makes the decision whether to represent data as boundary or as a complete region. Recognition is the process that assigns label to an object based on information provided by its descriptor.

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.

3.2 Image Segmentation Techniques

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

i. Thresholding based segmentation

ii. Region based segmentation

iii. Watershed segmentation

3.2.1 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'.

$$g(u,v) = \begin{cases} 1 & f(u,v) \geq T \\ 0 & otherwise \end{cases} \qquad (3.1)$$

Where T is predefined threshold. Selection of threshold is very crucial in image segmentation process. Threshold value can be determined either by an interactive way or can be the outcome of automatic threshold selection method. Otsu method is optimal for thresholding large objects from the background.

Threshold based approaches are computationally inexpensive fast and can be used for real time applications. A single global threshold partitions image into objects and background, but objects may have different characteristic gray value. In such situations multiple threshold values are needed, for applying over different areas of the image. Threshold value for each region is local threshold and the process is multilevel thresholding which helps to detect different objects in an image separately.

Steps for multilevel thresholding are:

1. Divide image into subparts.

2. Select local threshold for each subpart of image.

3. Compare the pixels for individual subpart and segment the region.

4. Repeat the process for each subpart and stop when all subparts are segmented.

Let us consider an image with two different objects, then identify two thresholds T1 and T2 such that

$$T1 \leq f(u,v) \leq T2 \quad \text{for one object}$$

$$f(u,v) \geq T2 \quad \text{for the other object}$$

$$f(u,v) \leq T1 \quad \text{for the background}$$

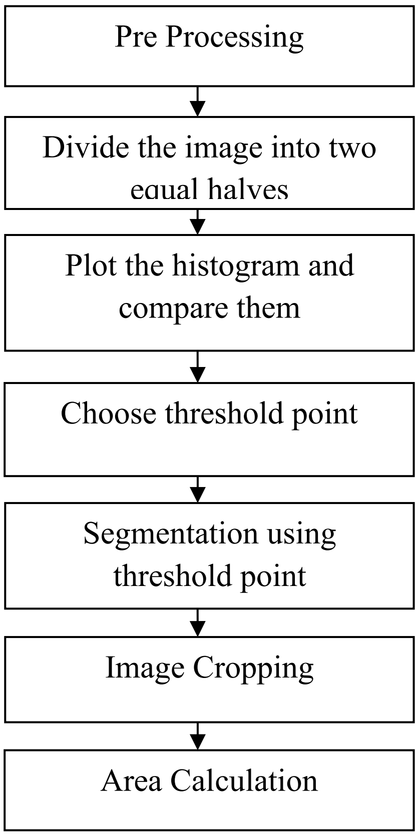


Fig 3.1 Thresholding Based Segmentation Flow

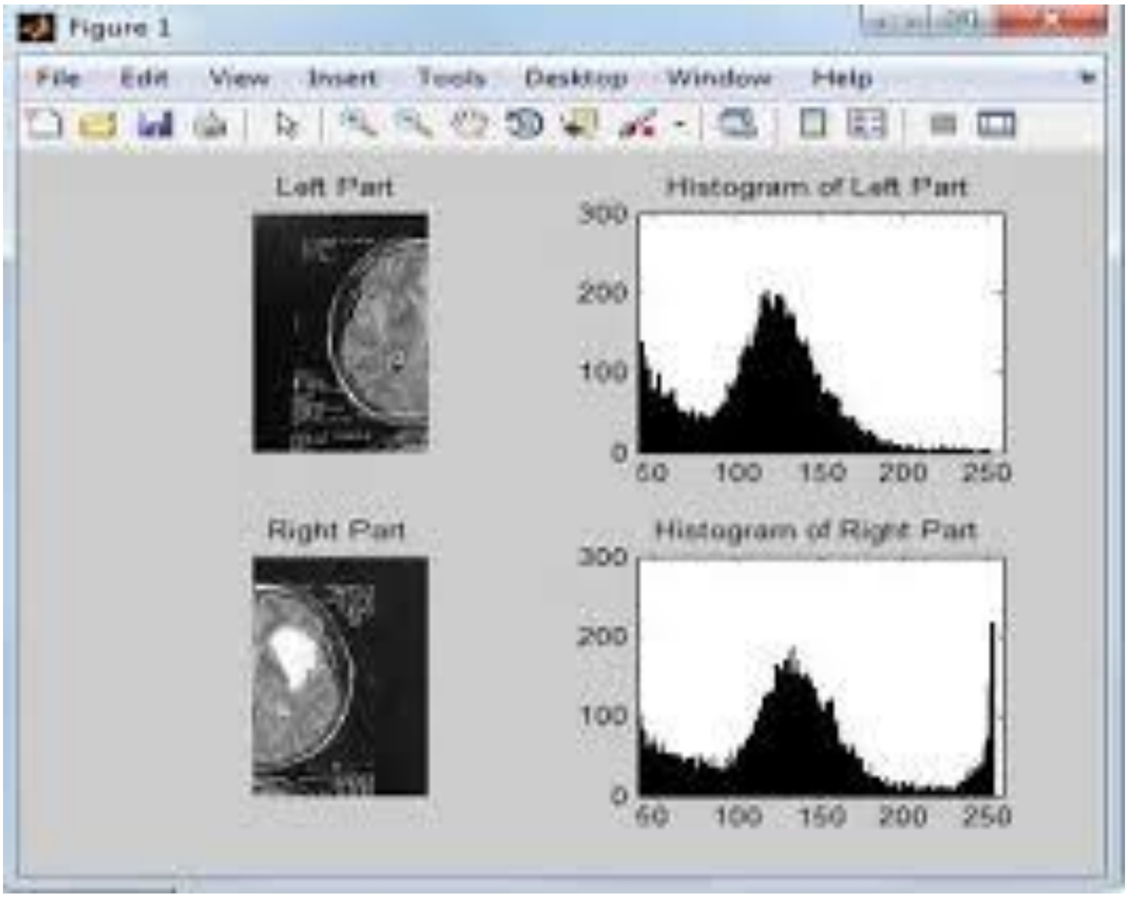


Fig 3.2 Separation of image and histogram of two sides

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..

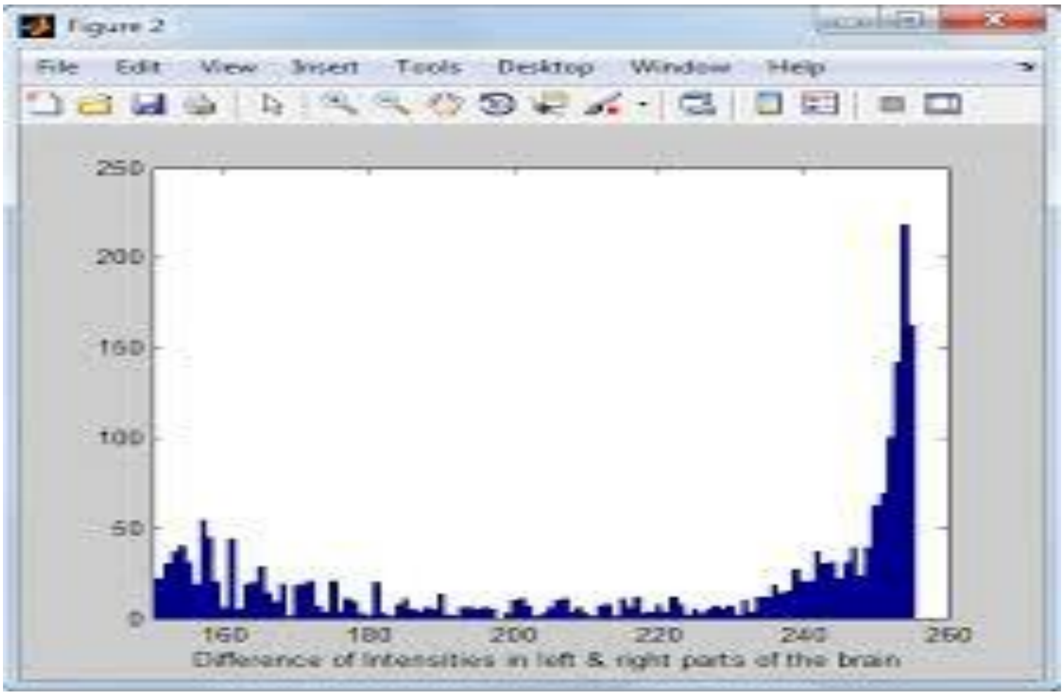


Fig 3.3 Difference in the intensity of the two side brain

The difference in the intensity of the two 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.

3.2.2 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.

CHAPTER 4

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:

- Clustering
- Edge detection
- Thresholding
- 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-based methods

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

- **Unsupervised** (calculated by software)
- 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 group age 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.

4.4 Initialization methods

Commonly used initialization methods are Forgy and Random Partition. The Forgy method randomly chooses *k* observations from the data set and uses these as the initial means. The Random Partition method first randomly assigns a cluster to each observation and then proceeds to the update step, thus computing the initial mean to be the centroid of the cluster's randomly assigned points. The Forgy method tends to spread the initial means out, while Random Partition places all of them close to the center of the data set. The Random Partition method is generally preferable for algorithms such as the k-harmonic means and fuzzy k-means. For expectation maximization and standard k-means algorithms, the Forgy method of initialization is preferable.

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.

- **Representation and Description**

Representation and description almost always follow the output of a segmentation stage, which usually is raw pixel data, constituting either the boundary of a region or all the points in the region itself. Choosing a representation is only part of the solution for transforming raw data into a form suitable for subsequent computer processing. Description deals with extracting attributes that result in some quantitative information of interest or for differentiating one class of objects from another.

- **Object recognition**

Recognition is the process that assigns a label to an object based on information provided by descriptors.

- **Knowledge Base**

Knowledge about a problem domain is coded into an image processing system in the form of a knowledge database.

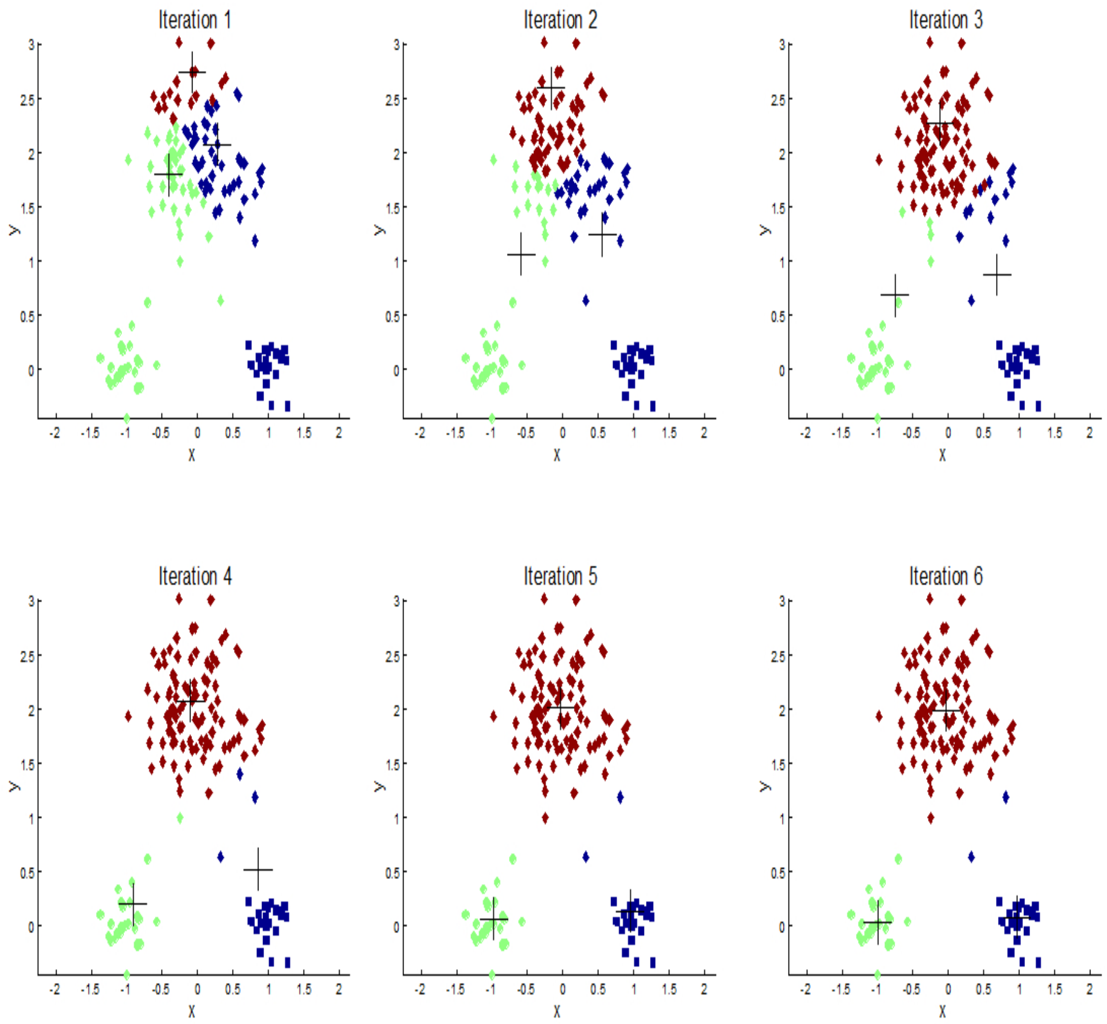


Fig 4.1 Different ways of clustering the same set of points

Fig 4.1 shows the different ways of clustering the same set of points. First choose the number of clusters as three .Choose randomly the three cluster centers.

Calculate the distance between each pixel to each cluster center. If the distance of pixel is near to the center the move to that cluster. Otherwise move to next cluster. Repeat the process until the center doesn't move.

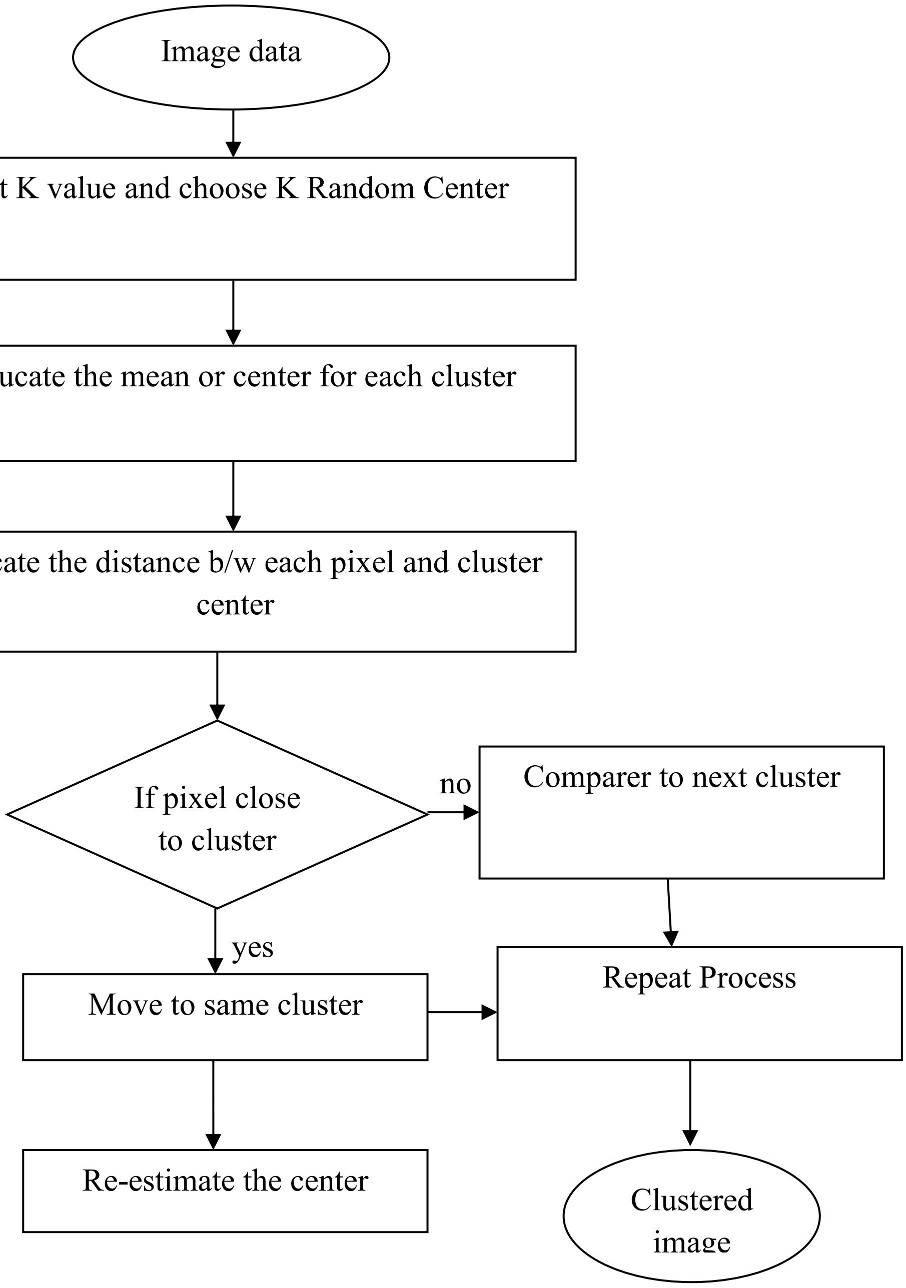


Fig 4.2 Flowchart for k-means Clustering

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

ALGORITHM:

The algorithmic steps involved for brain tumor shape detection is as follows,

Step 1: Start the process.

Step 2: Get the MRI scan image input in JPEG format.

Step 3: Check whether the input image is in required format and move to step 4 if not display error message.

Step 4: If image is in RGB format covert it into gray scale else move to next step.

Step 5: Find the edge of the grayscale image.

Step 6: Calculate the number of white points in the image.

Step 7: Calculate the size of the tumor using the formula.

Step 8: Display the size and stage of tumor.

Step 9: Stop the program.

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).

4.6 Feature Extraction

The feature extraction is extracting the cluster which shows the predicted tumor at the FCM output. The extracted cluster is given to the thresholding process. It applies binary mask over the entire image. It makes the dark pixel become darker and white become brighter. In threshold coding, each transform coefficient is compared with a threshold. If it is less than the threshold value then it is considered as zero. If it is larger than the threshold, it will be considered as one. The thresholding method is an adaptive method where only those coefficients whose magnitudes are above a threshold are retained within each block. Let us consider an image f that have the k gray level. An integer value of threshold T, which lies in the gray scale range of k. The thresholding process is a comparison. Each pixel in 'f 'is compared to T. Based on that, binary decision is made. That defines the value of the particular pixel in an output binary image 'g':

$$g(n) = \begin{cases} 0 \; if \; f(n) \geq T \\ 1 \; if \; f(n) < \; T \end{cases} \tag{4.6}$$

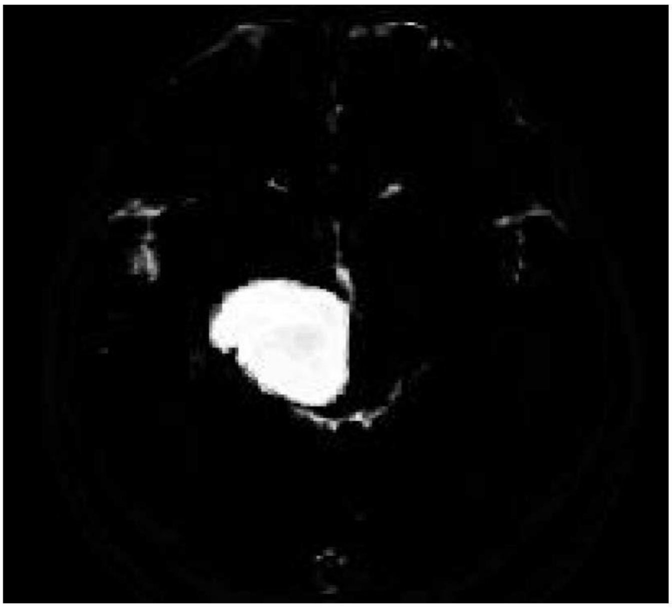


Fig 4.4 Output image of Thresholding

Fig 4.4 is the extracted tumor shape from the given image using the Fuzzy C- Means algorithm. The unpredicted tumor cells in the K-means algorithm

4.7 Area Calculation

The tumor area is calculated using the binarization method. That is the image having only two values either black or white (0 or 1).

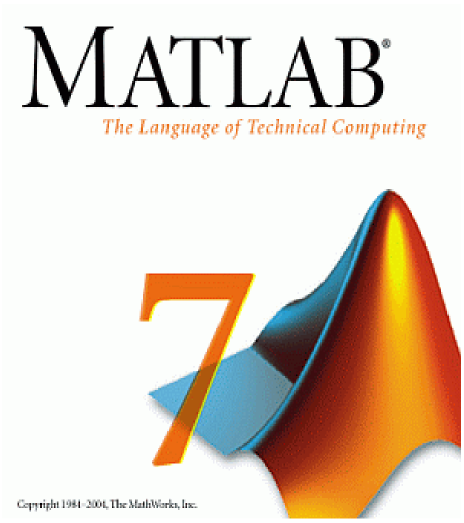
This algorithm scans the RGB or grayscale image, converts the image into binary image by binarization technique and detects the edge of tumor pixels in the binary image. Also it calculates the size of tumor by calculating the number of white pixels (digit 0) in binary image.

MATLAB

Introduction to MATLAB:

MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. Typical uses include

- Math and computation
- Algorithm development
- Data acquisition
- Modeling, simulation, and prototyping
- Data analysis, exploration, and visualization
- Scientific and engineering graphics
- Application development, including graphical user interface building



Fig

MATLAB is an interactive system whose basic data element is an array that does not require dimensioning. This allows you to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar non interactive language such as C or FORTRAN.

The name MATLAB stands for matrix laboratory. MATLAB was originally written to provide easy access to matrix software developed by the LINPACK and EISPACK projects. Today, MATLAB engines incorporate the LAPACK and BLAS libraries, embedding the state of the art in software for matrix computation.

MATLAB has evolved over a period of years with input from many users. In university environments, it is the standard instructional tool for introductory and advanced courses in mathematics, engineering, and science. In industry, MATLAB is the tool of choice for high-productivity research, development, and analysis.

MATLAB features a family of add-on application-specific solutions called toolboxes. Very important to most uses of MATLAB, toolboxes allow you to learn and apply specialized technology. Toolboxes are comprehensive collections of MATLAB functions (M – files) that extend the MATLAB environment to solve particular classes of problems. Areas in which toolboxes are available include signal processing, control systems, neural networks, fuzzy logic, wavelets, simulation, and many others.

The MATLAB system:

The MATLAB system consists of five main parts

- **Development Environment**:

This is the set of tools and facilities that help you use MATLAB functions and files. Many of these tools are graphical user interfaces. It includes the MATLAB desktop and command window, a command history, an editor and debugger, and browsers for viewing help, the workspace, files, and the search path.

- **The MATLAB Mathematical Function Library**:

This is a vast collection of computational algorithms ranging from elementary functions, like sum, sine, cosine, and complex arithmetic, to more sophisticated functions like matrix inverse, matrix Eigen values, Bessel functions, and fast Fourier transforms.

- **The MATLAB Language**:

This is a high-level matrix/array language with control flow statements, functions, data structures, input/output, and object-oriented programming features. It allows both "programming in the small" to rapidly create quick and dirty throw-away programs, and "programming in the large" to create large and complex application programs.

In the item part MATLAB programming and the highlight, which is to be settled, is the base need. A rate of the points of interest from MATLAB in highlight taking care of are:

- Easy to work with; as Images are lattices
- Built in capacities for complex operations and calculations (Ex. FFT, DCT, and so forth…)
- Image transforming tool kit,
- Supports most picture configurations (.bmp, .jpg, .gif, tiff and so forth…)

4. 8 INTRODUCTION TO MATLAB

MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. MATLAB stands for matrix laboratory, and was written originally to provide easy access to matrix software developed by LINPACK (linear system package) and EISPACK (Eigen system package) projects. MATLAB is therefore built on a foundation of sophisticated matrix software in which the basic element is array that does not require pre dimensioning which to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of time.

MATLAB features a family of applications specific solutions called toolboxes. Very important to most users of MATLAB, toolboxes allow learning and applying specialized technology. These are comprehensive collections of MATLAB functions (M-files) that extend the MATLAB environment to solve particular classes of problems. Areas in which toolboxes are available include signal processing, control system, neural networks, fuzzy logic, wavelets, simulation and many others.

Typical uses of MATLAB include: Math and computation, Algorithm development, Data acquisition, Modeling, simulation, prototyping, Data analysis, exploration, visualization, Scientific and engineering graphics, Application development, including graphical user interface building.

MATLAB is a program that was originally designed to simplify the implementation of numerical linear algebra routines. It has since grown into something much bigger, and it is used to implement numerical algorithms for a wide range of applications. The basic language used is very similar to standard linear algebra notation, but there are a few extensions that will likely cause you some problems at first.

Basic Building Blocks of MATLAB

The basic building block of MATLAB is MATRIX. The fundamental data type is the array. Vectors, scalars, real matrices and complex matrix are handled as specific class of this basic data type. The built in functions are optimized for vector operations. No dimension statements are required for vectors or arrays.

MATLAB Window

The MATLAB works based on five windows: Command window, Workspace window, Current directory window, Command history window, Editor Window, Graphics window and Online-help window.

Command Window

The command window is where the user types MATLAB commands and expressions at the prompt (>>) and where the output of those commands is displayed. It is opened when the application program is launched. All commands including user-written programs are typed in this window at MATLAB prompt for execution.

Work Space Window

MATLAB defines the workspace as the set of variables that the user creates in a work session. The workspace browser shows these variables and some information about them. Double clicking on a variable in the workspace browser launches the Array Editor, which can be used to obtain information.

Current Directory Window

The current Directory tab shows the contents of the current directory, whose path is shown in the current directory window. For example, in the windows operating system the path might be as follows: C:\MATLAB\Work, indicating that directory “work” is a subdirectory of the main directory “MATLAB”; which is installed in drive C. Clicking on the arrow in the current directory window shows a list of recently used paths. MATLAB uses a search path to find M-files and other MATLAB related files. Any file run in MATLAB must reside in the current directory or in a directory that is on search path.

Command History Window

The Command History Window contains a record of the commands a user has entered in the command window, including both current and previous MATLAB sessions. Previously entered MATLAB commands can be selected and re-executed from the command history window by right clicking on a command or sequence of commands. This is useful to select various options in addition to executing the commands and is useful feature when experimenting with various commands in a work session.

Editor Window

The MATLAB editor is both a text editor specialized for creating M-files and a graphical MATLAB debugger. The editor can appear in a window by itself, or it can be a sub window in the desktop. In this window one can write, edit, create and save programs in files called M-files.

MATLAB editor window has numerous pull-down menus for tasks such as saving, viewing, and debugging files. Because it performs some simple checks and also uses color to differentiate between various elements of code, this text editor is recommended as the tool of choice for writing and editing M-functions.

Graphics or Figure Window

The output of all graphic commands typed in the command window is seen in this window.

Online Help Window

MATLAB provides online help for all it's built in functions and programming language constructs. The principal way to get help online is to use the MATLAB help browser, opened as a separate window either by clicking on the question mark symbol (?) on the desktop toolbar, or by typing help browser at the prompt in the command window. The help Browser is a web browser integrated into the MATLAB desktop that displays a Hypertext Markup Language (HTML) documents. The Help Browser consists of two panes, the help navigator pane, used to find information, and the display pane, used to view the information. Self-explanatory tabs other than navigator pane are used to perform a search.

4.9 GRAPHICAL USER INTERFACE (GUI):

MATLAB's Graphical User Interface Development Environment (GUIDE) provides a rich set of tools for incorporating graphical user interfaces (GUIs) in M-functions. Using GUIDE, the processes of laying out a GUI (i.e., its buttons, pop-up menus, etc.)and programming the operation of the GUI are divided conveniently into two easily managed and relatively independent tasks. The resulting graphical M-function is composed of two identically named (ignoring extensions) files:

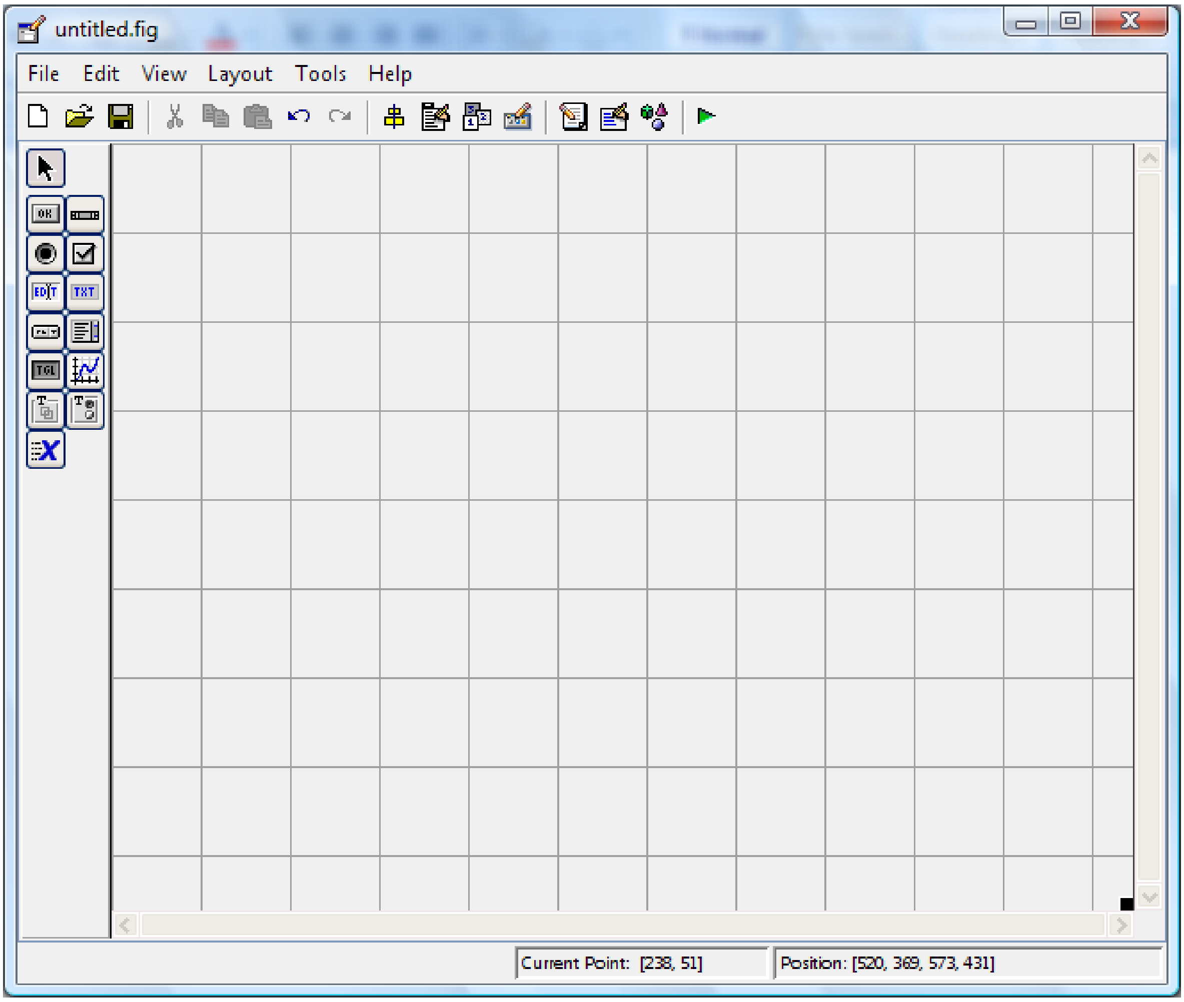
- A file with extension .fig, called a FIG-file that contains a complete graphical description of all the function's GUI objects or elements and their spatial arrangement. A FIG-file contains binary data that does not need to be parsed when he associated GUI-based M-function is executed.

- A file with extension .m, called a GUI M-file, which contains the code that controls the GUI operation. This file includes functions that are called when the GUI is launched and exited, and callback functions that are executed when a user interacts with GUI objects for example, when a button is pushed.

To launch GUIDE from the MATLAB command window, type guide filename

Where filename is the name of an existing FIG-file on the current path. If filename is omitted,

GUIDE opens a new (i.e., blank) window.


untitled.fig
File Edit View Layout Tools Help
Current Point: [238, 51]
Position: [520, 369, 573, 431]

4.10 SOURCE CODE

```
function varargout = gui(varargin)

gui_Singleton = 1;

gui_State = struct('gui_Name',  mfilename, ...

                   'gui_Singleton', gui_Singleton, ...

                   'gui_OpeningFcn', @gui_OpeningFcn, ...

                   'gui_OutputFcn', @gui_OutputFcn, ...

                   'gui_LayoutFcn', [], ...

                   'gui_Callback', []);

if nargin && ischar(varargin{1})

    gui_State.gui_Callback = str2func(varargin{1});

end

if nargout

    [varargout{1:nargout}] = gui_mainfcn(gui_State, varargin{:});

else

    gui_mainfcn(gui_State, varargin{:});

end

function gui_OpeningFcn(hObject, eventdata, handles, varargin)

handles.output = hObject;

a = ones(256,256);

axes(handles.axes1);

imshow(a);
```

```
axes(handles.axes2);
imshow(a);
axes(handles.axes4);
imshow(a);
set(handles.text1,'string','');
guidata(hObject, handles);
 function varargout = gui_OutputFcn(hObject, eventdata, handles)
varargout{1} = handles.output;
function Browse_im_Callback(hObject, eventdata, handles)
cd timages
   [file,path] = uigetfile('*.jpg;*.bmp;*.gif;*.png', 'Pick an Image File');
   im = imread(file);
cd ..
   im=imresize(im,[256 256]);
  if size(im,3)>1
      im = rgb2gray(im);
   end
   axes(handles.axes1);
   imshow(im);
   title('Input MRI Brain Image');
 handles.im = im;
 guidata(hObject, handles);
```

```
('Test Image Selected');

function database_load_Callback(hObject, eventdata, handles)

nnlearn;

function classify_im_Callback(hObject, eventdata, handles)

load qfeat;

load netp;

cout = sim(netp,qfeat);

cout = vec2ind(cout);

 if isequal(cout,1)

  set(handles.text6,'String','Stage :');

  set(handles.text1,'String','Brain Tumor 0% Effected [Normal]');

  elseif isequal(cout,2)

  set(handles.text6,'String','Stage :');

  set(handles.text1,'String','Brain Tumor 30% Effected [BENIGN]');

   elseif isequal(cout,3)

  set(handles.text6,'String','Stage :');

  set(handles.text1,'String','Brain Tumor 50% Effected [MALIGNANT]');

  else

  helpdlg('Db updation required');

  end

  handles.result = cout;

  guidata(hObject,handles);
```

```
function transform_Callback(hObject, eventdata, handles)
 im = handles.im;
[LL LH HL HH] = dwt2(im,'db1');  %% HAAR,DB,Bi.ortho
aa = [LL LH;HL HH];
[LL1 LH1 HL1 HH1] = dwt2(LL,'db1');
 aa1 = [LL1 LH1;HL1 HH1];
[LL2 LH2 HL2 HH2] = dwt2(LL1,'db1');
[LL3 LH3 HL3 HH3] = dwt2(LL2,'db1');
aa1 = [LL3 LH3;HL3 HH3];
aa2 = [aa1 LH2;HL2 HH2];
aa3 = [aa2 LH1;HL1 HH1];
aa4  = [aa3 LH;HL HH];
axes(handles.axes2);
imshow(aa2,[]);
title('Discrete Wavelet Transform Image');
LH3 = uint8(LH3);
Min_val = min(min(LH3));
Max_val = max(max(LH3));
level = round(Max_val - Min_val);
GLCM = graycomatrix(LH3,'GrayLimits',[Min_val Max_val],'NumLevels',level);
stat_feature = graycoprops(GLCM);
Energy_fet1 = stat_feature.Energy;
```

```
Contr_fet1 = stat_feature.Contrast;
Corrla_fet1 = stat_feature.Correlation;
Homogen_fet1 = stat_feature.Homogeneity;
 R = sum(sum(GLCM));
  Norm_GLCM_region = GLCM/R;
  Ent_int = 0;
  for k = 1:length(GLCM)^2
   if Norm_GLCM_region(k)~=0
    Ent_int = Ent_int + Norm_GLCM_region(k)*log2(Norm_GLCM_region(k));
            end
        end
    Entropy_fet1 = -Ent_int;
 HL3 = uint8(HL3);
Min_val = min(min(HL3));
Max_val = max(max(HL3));
level = round(Max_val - Min_val);
GLCM = graycomatrix(HL3,'GrayLimits',[Min_val Max_val],'NumLevels',level);
stat_feature = graycoprops(GLCM);
Energy_fet2 = stat_feature.Energy;
Contr_fet2 = stat_feature.Contrast;
Corrla_fet2= stat_feature.Correlation;
Homogen_fet2 = stat_feature.Homogeneity;
```

```
R = sum(sum(GLCM));
Norm_GLCM_region = GLCM/R;
Ent_int = 0;
    for k = 1:length(GLCM)^2
      if Norm_GLCM_region(k)~=0
        Ent_int = Ent_int + Norm_GLCM_region(k)*log2(Norm_GLCM_region(k));
      end
    end
Entropy_fet2 = -Ent_int;
F1 = [Energy_fet1 Contr_fet1 Corrla_fet1 Homogen_fet1 Entropy_fet1];
F2 = [Energy_fet2 Contr_fet2 Corrla_fet2 Homogen_fet2 Entropy_fet2];
 qfeat = [F1 F2]';
save qfeat qfeat;
 disp('Query Features: ');
disp(qfeat);
function close_Callback(hObject, eventdata, handles)
delete *.mat;
close all;
function clear_Callback(hObject, eventdata, handles)
clc;
set(handles.text1,'string','');
set(handles.text6,'string','');
```

```
set(handles.text7,'string','');
set(handles.text8,'string','');
set(handles.text9,'string','');
 a = ones(256,256);
axes(handles.axes1);
imshow(a);
axes(handles.axes2);
imshow(a);
clear all;
function validate_Callback(hObject, eventdata, handles)
Tp = 3; Fn = 2;
 Fp = 2; Tn = 3;
Sensitivity = (Tp./(Tp+Fn)).*100;
Specificity = (Tn./(Tn+Fp)).*100;
Accuracy = ((Tp+Tn)./(Tp+Tn+Fp+Fn)).*100;
 figure('Name','Performance Metrics','MenuBar','none');
bar3(1,Sensitivity,0.3,'m');
hold on;
bar3(2,Specificity,0.3,'r');
hold on;
bar3(3,Accuracy,0.3,'g');
hold off;
```

```
xlabel('Parametrics--->');
zlabel('Value--->');
legend('Sensitivity','Specificity','Accuracy');
 disp('Sensitivity: '); disp(Sensitivity);
disp('Specificity: '); disp(Specificity);
disp('Accuracy:'); disp(Accuracy);
function segment_Callback(hObject, eventdata, handles)
result =handles.result;
 inp = handles.im;
 if result ==1
 warndlg ('No Tumor');
 elseif result ==2
 [segout,tarea] = BSegment(inp);
 boundary = bwboundaries(im2bw(segout));
  axes(handles.axes1);
  imshow(inp); title('Tumor Area Localization');
  hold on;
  for ii=1:1:length(boundary)
      btemp = boundary{ii};
      plot(btemp(:,2),btemp(:,1),'r','LineWidth',4);
  end
  hold off;
```

```
  axes(handles.axes4);
  imshow(segout);
  title('Brain Segmented Image');
  set(handles.text7,'String','Area :');
  set(handles.text8,'String',tarea);
  set(handles.text9,'String','mm.^2');
  handles.area = tarea;
  guidata(hObject,handles);
  elseif result ==3
  [segout,tarea] = MSegment(inp);
boundary = bwboundaries(im2bw(segout));
axes(handles.axes1);
imshow(inp); title('Tumor Area Localization');
hold on;
for ii=1:1:length(boundary)
btemp = boundary{ii};
      plot(btemp(:,2),btemp(:,1),'r','LineWidth',4);
   end
   hold off;
axes(handles.axes4);
imshow(segout);
   title('Brain Segmented Image');
```

```
set(handles.text7,'String','Area :');

set(handles.text8,'String',tarea);

set(handles.text9,'String','mm.^2');

 handles.area = tarea;

 guidata(hObject,handles);

 end

function pushbutton17_Callback(hObject, eventdata, handles)

function edit2_Callback(hObject, eventdata, handles)

function edit2_CreateFcn(hObject, eventdata, handles)

if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))

    set(hObject,'BackgroundColor','white');

end
```

CHAPTER 5

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.

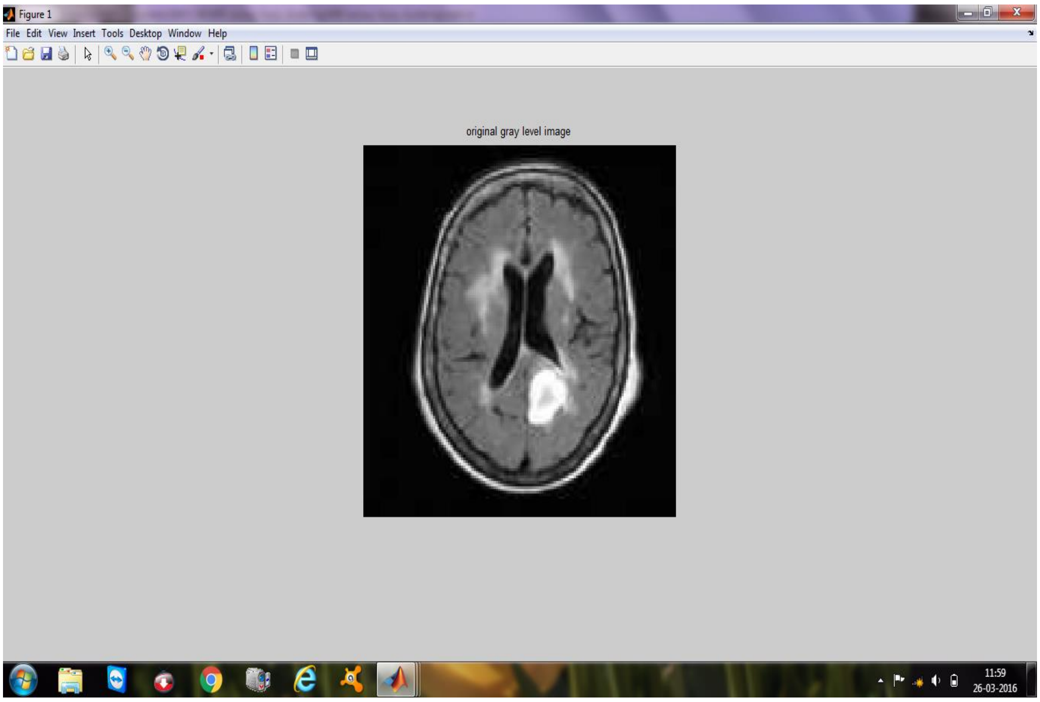


Fig 5.1 Original gray level image

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.

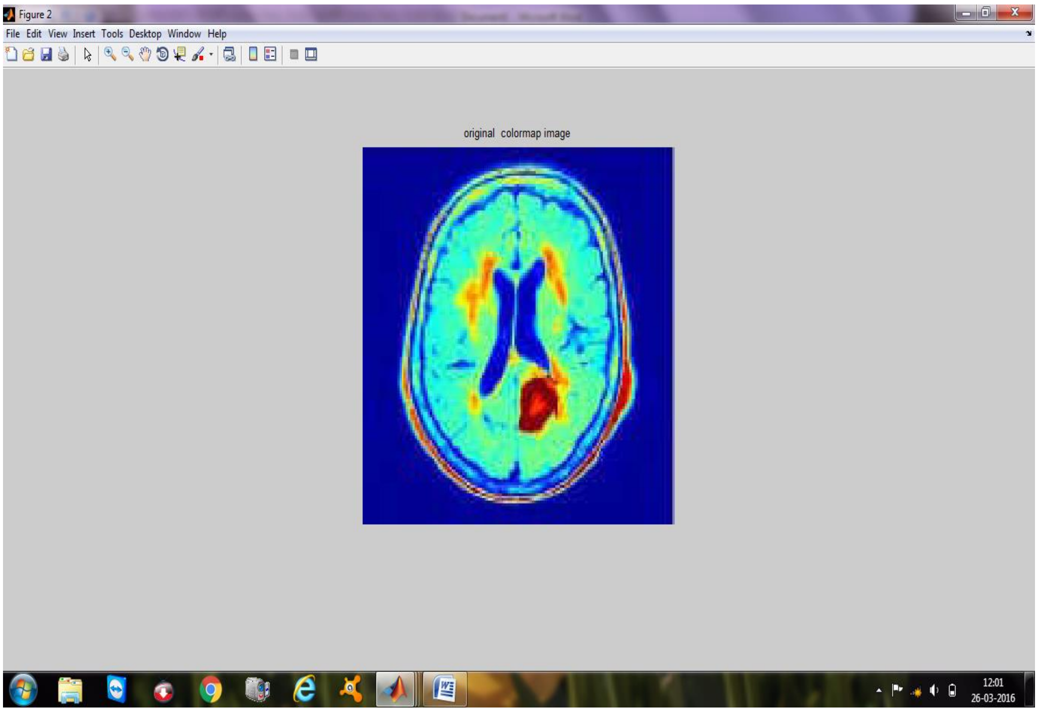


Fig 5.2 Original colormap image

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

k-mean clustering algorithm is applied to the color space translated image. In k-means clustering k represents the number of clusters .In this, the pixels in the image are divided into three clusters. The output thus obtained has three clusters (Black,White and grey) as shown in Fig 5.4 .The output image has a size of 144x144 and of bmp format.

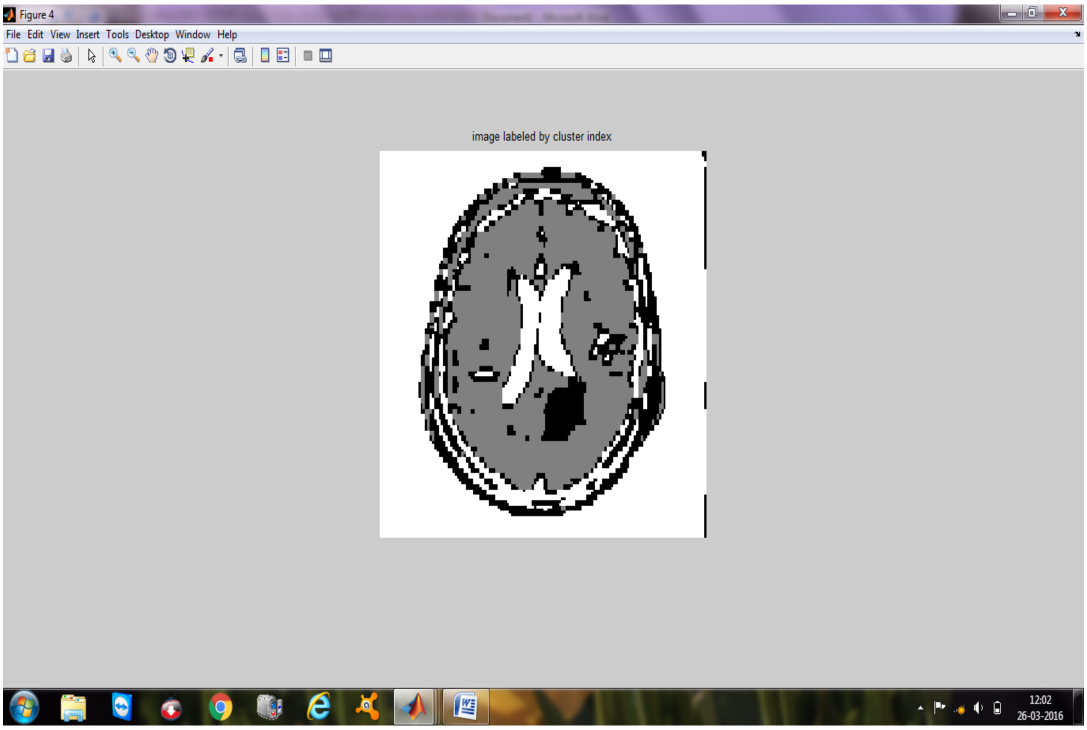


Fig 5.4 Image labelled by cluster index

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.

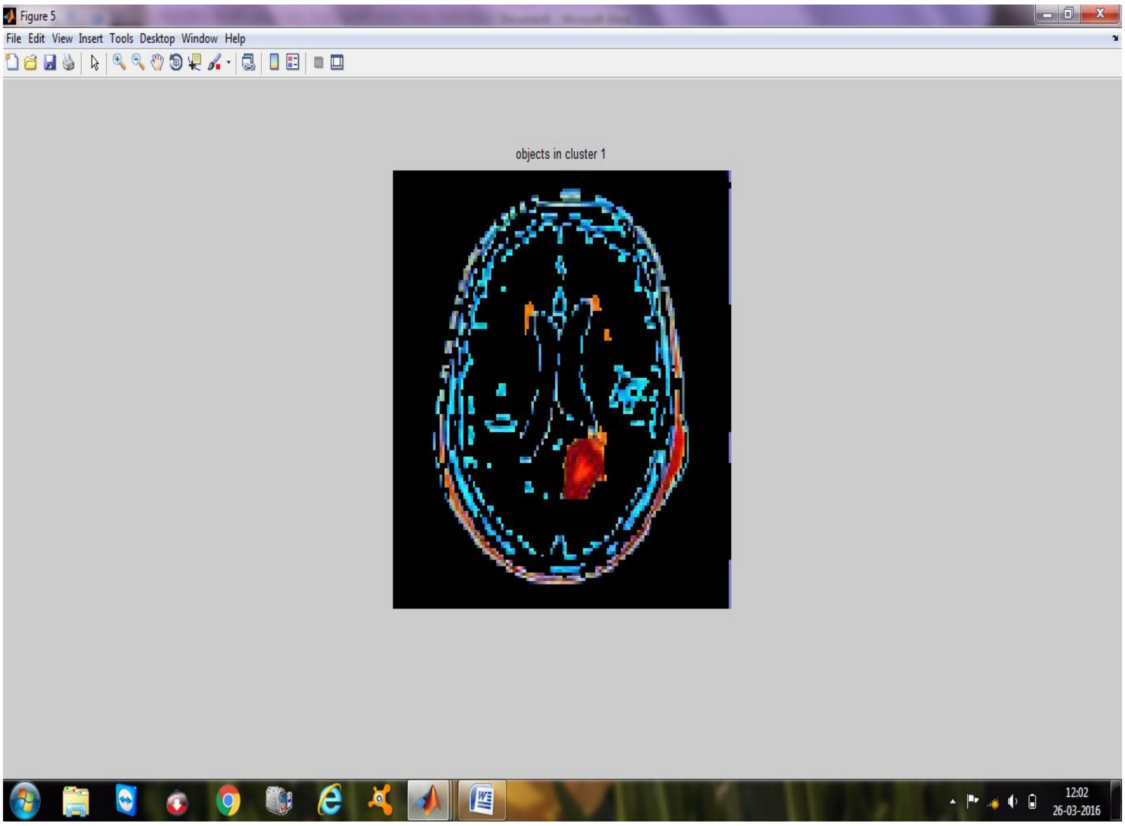


Fig 5.5 Objects in cluster 1

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.

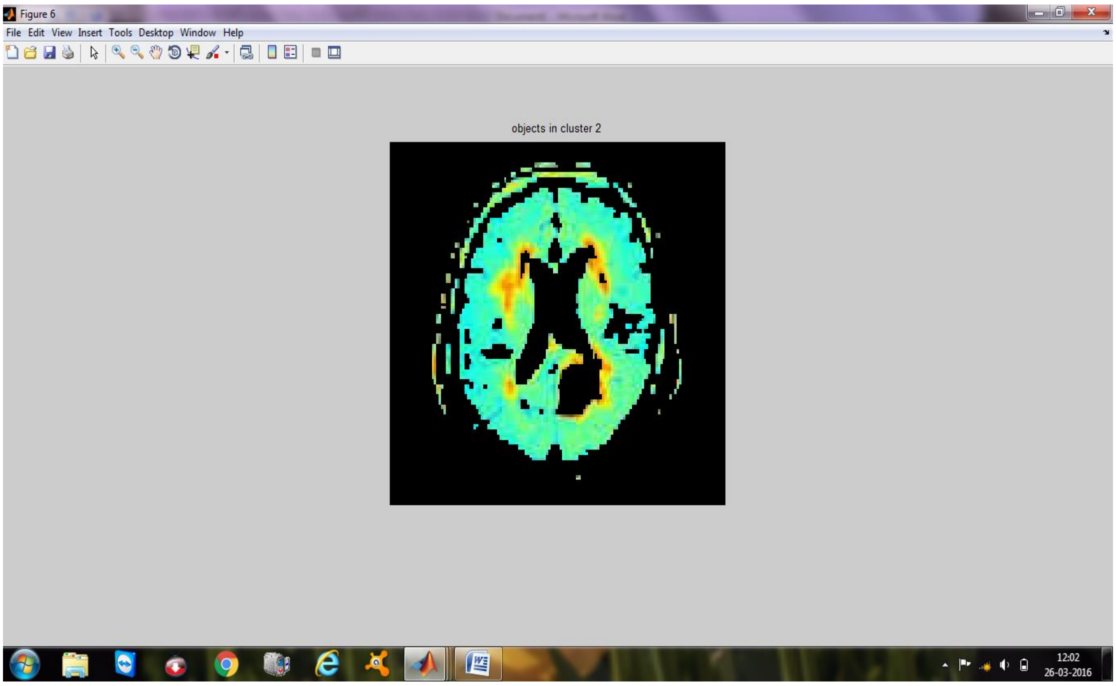


Fig 5.6 Objects in cluster 2

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.

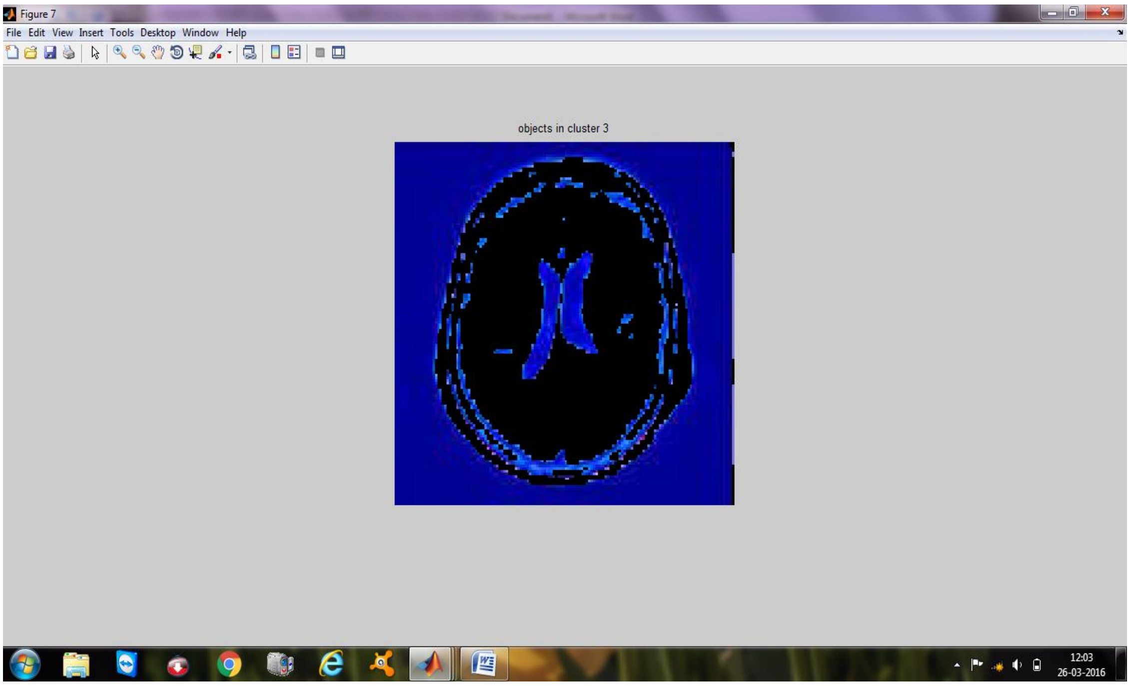


Fig 5.7 Objects in cluster 3

Once the clustering is done by using k-mean algorithm the tumor gets extracted from the brain as shown in Fig 5.8. Once the tumor gets extracted the area of tumor is calculated .The area of tumor is 4.1992

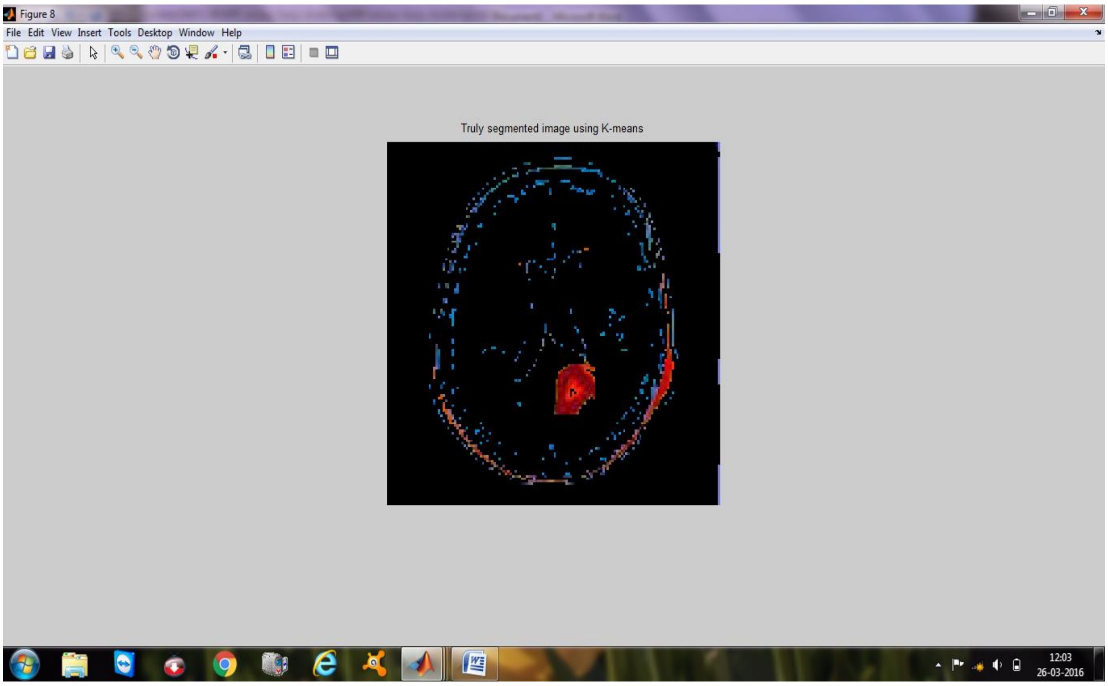


Fig 5.8 Truly segmented image using k-means

PARAMETER	K-MEAN	
Area	4.1992	

Table 5.1 Comparison between K-Mean and FCM

5.2 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.

5.3 BIBLIOGRAPHY

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