

SEGMENTATION ON MRI BRAIN IMAGE AND CLASSIFICATION OF STAGES OF TUMOR USING MACHINE LEARNING

Submitted in partial fulfilment of the requirements for the award of

**Bachelor of Engineering degree in
Computer Science and Engineering**

BY

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

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INSTITUTE OF SCIENCE AND TECHNOLOGY

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CHENNAI - 600 119

MAY - 2022



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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **MOHAMMAD AFTAB AHMED - (38110321), MEKA KESAVARDHAN - (38110319)** who carried out the project entitled “**SEGMENTATION ON MRI BRAIN IMAGE AND CLASSIFICATION OF STAGES OF TUMOR USING MACHINE LEARNING**” under my supervision from AUG 2021 to MARCH 2022.

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ABSTRACT

The improvement of technology and Machine Learning can help radiologists in tumor diagnostics without invasive measures. A Machine-learning algorithm that has achieved substantial results in image segmentation and classification is the convolutional neural network (CNN). A new CNN architecture is proposed for brain tumor classification of three stages of tumor types. Initially, the image is filtered using 2D Adaptive Median Filter (2D-AMF) for noise removal. The de-noised image is then enhanced using Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm. From the enhanced image, the Region Of Interest (ROI) is segmented using clustering and threshold methods. Clustering is performed using Fast Fuzzy C Means Clustering (FFCM) and threshold is performed using Otsu threshold (OT) algorithm. From the ROI, features are extracted using Gray Level Co-Occurrence Matrix (GLCM). GLCM is a feature that computes the occurrence of pixel pairs in specific spatial coordinates of an image. Finally, the obtained features are classified using machine learning based Convolutional Neural Network (CNN) techniques.

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CHAPTER 1

INTRODUCTION

We propose another technique for deformable enlistment of pre-usable and post-repeat mind MR sweeps of patients. Playing out this sort of intra-subject enlistment is trying as Alzheimer, resection, repeat, and edema cause enormous misshapenings, missing correspondences, and conflicting force profiles between the outputs. Populace investigation of cerebrum morphology from attractive reverberation pictures adds to the examination and comprehension of neurological infections. Such investigation ordinarily includes division of an enormous arrangement of pictures and correlations of these divisions between significant subgroups of pictures (e.g., "typical" versus "sick").

The pictures of every subgroup are normally chosen ahead of time in a regulated manner dependent on clinical information. Their divisions are commonly guided by at least one accessible map books, thought to be appropriate for the current pictures. Bunching approach is broadly utilized in biomedical applications especially for cerebrum tumor identification in unusual attractive reverberation (MRI) pictures.

Fuzzy clustering using modified fuzzy C-means (FCM) calculation end up being better preposterous bunching approaches as far as division proficiency. Yet, the significant disadvantage of the changed FCM calculation is the enormous computational time needed for intermingling. The viability of the adjusted FCM calculation as far as computational rate is improved by changing the group community and participation esteem refreshing model.

In this paper, the utilization of adjusted FCM calculation for MR cerebrum tumor identification is investigated. An extensive element vector space is utilized for the division method. Near investigation as far as division effectiveness and combination rate is performed between the traditional FCM and the changed FCM. Exploratory outcomes show unrivaled outcomes for the changed FCM calculation as far as the exhibition measures.

1.1 OBJECTIVES

- To develop an Efficient Alzheimer's disease segmentation on MRI brain image and classification of stages of tumor using machine learning

Detailed Objectives:

- Initially, the image is filtered using 2D Adaptive Median Filter (2D-AMF) for noise removal.
- The de-noised image is then enhanced using Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm.

- From the enhanced image, the Region Of Interest (ROI) is segmented using clustering and threshold methods.
- Clustering is performed using Fast Fuzzy C Means Clustering (FFCM) and threshold is performed using Otsu threshold (OT) algorithm.
- From the ROI, features are extracted using Gray Level Co-Occurrence Matrix (GLCM).
- GLCM is a feature that computes the occurrence of pixel pairs in specific spatial coordinates of an image.
- Finally, the obtained features are classified using machine learning based Convolutional Neural Network (CNN) techniques.

1.2 EXISTING SYSTEM

Force based Region-developing division

1.2.1 DISADVANTAGES OF EXISTING ALGORITHM

- The locale developing division isn't liked for its restricted scope of utilizations and programmed highlights are not having precise qualities.
- Preprocessing tests are expected to discover which kind of sifting will be more advantageous. This builds the impact of the dot clamor and Gaussian commotion the ultrasound, mammogram Images and MRI Images.
- The wanted Alzheimer territory is chosen from the portioned picture to ascertain the volume. The volume of the ideal Alzheimer zone is more noteworthy than the first Alzheimer region. The locale developing calculation will fragment the Alzheimer zone as well as the non-Alzheimer territory which has extreme focus proportion.
- This calculation completely relies upon the force of the picture not the shape and surface. So the exactness and affectability is low.

1.3 PROPOSED SYSTEM

Preprocessing

Algorithm 1

1.3.1 Image Restoration

Proposed Algorithm 1

(Image Pre-processing Step 1 – Image Denoising (Restoration))

Image De-noising utilizing Anisotropic Diffusion combination Filter

The least difficult and best explored dissemination strategy for smoothing pictures is to apply a straight dispersion measure. We will zero in on the connection between straight dissemination separating and the convolution with a Gaussian, investigate its smoothing properties for the picture just as its subordinates, and survey the major properties of the Gaussian scale-space incited by direct dispersion sifting.

Proposed Algorithm 2

1.3.2 Image Enhancement

Image Enhancement utilizing Contrast Limited Adaptive Histogram Equalization (CLAHE calculation)

a) Adaptive histogram adjustment

(AHE) is a PC picture handling strategy used to improve contrast in pictures. It varies from customary histogram leveling in the regard that the versatile technique processes a few histograms, each comparing to a particular segment of the picture, and uses them to reallocate the gentility estimations of the picture. It is subsequently appropriate for improving the neighborhood difference of a picture and bringing out more detail. In any case, AHE tends to over-enhance commotion in moderately homogeneous districts of a picture. A variation of versatile histogram balance called contrast restricted versatile histogram balance (CLAHE) forestalls this by restricting the intensification.

Head part examination (PCA) is a factual technique that utilizes a symmetrical change to change over a bunch of perceptions of potentially associated factors into a bunch of estimations of directly uncorrelated factors called head segments. PCA is the least complex of the genuine eigenvector-based multivariate examinations. Regularly, its activity can be considered as uncovering the interior construction of the information such that best clarifies the change in the information. PCA is numerically characterized as a symmetrical direct change that changes the information to another organize framework to such an extent that the best fluctuation by some projection of the information comes to lie on the main arrange (called the primary head segment), the second most prominent difference on the subsequent facilitate, etc.

b) Contrast Enhancement

There is a solid impact of differentiation proportion on settling force and recognition capacity of pictures. Strategies for improving picture contrast are among the most broadly utilized upgrade measures. The affectability scope of any distant detecting locator is intended to record a wide scope of territory brilliance from dark basalt levels to White Sea beds under a wide scope of lighting conditions. Barely any individual scenes have a brilliance range that uses the full sensitivity scope of these identifiers. To deliver a picture with the ideal differentiation proportion, it is imperative to utilize the whole brilliance scope of the presentation medium, which is for the most part film.

The motivation behind picture reclamation is to "make up for" or "fix" deserts which debase a picture. Corruption comes in numerous structures, for example, movement obscure, commotion, and camera misfocus. In cases like movement obscure, it is feasible to concoct an awesome gauge of the real obscuring capacity and "fix" the haze to reestablish the first picture. In situations where the picture is defiled by commotion, the best we may want to do is to make up for the corruption it caused. In this task, we will present and execute a few of the strategies utilized in the picture preparing world to reestablish pictures.

1.4 Degradation Model

The block diagram for our general degradation model is

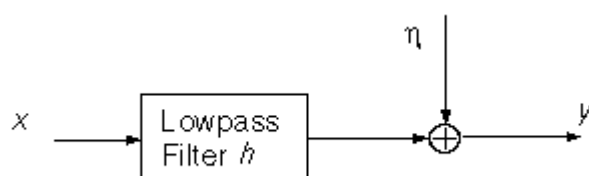


Fig. 1.1: block diagram of general degradation model

where g is the corrupted picture gotten by passing the first picture f through a low pass channel (obscuring function) b and adding clamor to it.

To comprehend what is the issue here, one first requirements to comprehend what a middle channel is and what it does. In a wide range of sorts of advanced picture handling, the fundamental activity is as per the following: at every pixel in a computerized picture we place a neighborhood around that point, break down the estimations of the relative multitude of pixels in the area as indicated by some calculation, and afterward supplant the first pixel's worth with one dependent on the investigation performed on the pixels in the area. The local at that point moves progressively over each pixel in the picture, rehashing the interaction.

The BDND calculation initially orders the pixels of a restricted window, focusing on the current pixel, into three gatherings lower force motivation commotion, uncorrupted pixels, and higher power drive clamor. The middle pixel will at that point be considered as uncorrupted, given that it has a place with the uncorrupted pixel bunch, or undermined. For that, two limits that segregate these three gatherings need to be precisely decided for yielding high commotion identification exactness.

The BDND calculation is applied to every pixel of the boisterous picture to distinguish whether it is uncorrupted or tainted. After such an application to the whole picture, a two-dimensional paired choice guide is shaped toward the finish of the clamor recognition stage, with 0s showing the places of uncorrupted pixels, and 1s for those tainted ones.

To achieve this evenhanded, every one of the pixels inside a pre-characterized window that middle on the considered pixel will be assembled into three bunches; consequently, two limits b_1 and b_2 are needed to be resolved. For every pixel being thought of, if $0 \leq x_{i,j} \leq b_1$, the pixel will be relegated to the lower-power group; in any case, to the medium-force bunch for $b_1 < x_{i,j} \leq b_2$ or to the focused energy group for $b_2 < x_{i,j} \leq 255$. Clearly, if the middle pixel being viewed as falls onto the center group, it will be treated as uncorrupted, since its power esteem is neither generally low nor moderately high. Else, all things considered, the pixel has been defiled by motivation clamor. Unmistakably, the precision of bunching results (subsequently, the exactness of commotion identification) at last relies upon how exact the recognized limits b_1 and b_2 are.

The limit discriminative cycle comprises of two emphasis, in which the subsequent emphasis might be summoned restrictively. In the principal emphasis, a broadened neighborhood window with a size of 21×21 (exactly decided) is utilized to analyze whether the considered pixel is an uncorrupted one.

Clamor is any undesired data that sullies a picture. Motivation commotion is an extraordinary sort of clamor, which have a wide range of roots. The Salt and Pepper type drive clamor is ordinarily brought about by breaking down of the pixel components in the camera sensors, broken memory areas, or timing mistakes in the digitization interaction. For the pictures debased by Salt and Pepper clamor, the boisterous pixels can take just the most extreme or the base qualities in the powerful reach.

An important non linear filter that will preserve the edges and remove impulse noise is standard median filter Median (SMF). It replaces every pixel by its median value from its neighborhood and often removes desirable details in the image. Specialized median filter such as weighted median filter (WMF) were proposed to improve the performance of median filter by giving more weight to some selected pixel in the filtering window. But they still implemented uniformly across the images without considering the current pixel whether is noisy or noise free. Therefore, a noise-detection process to discriminate between uncorrupted pixels and corrupted pixels is highly desirable. Some of decision based algorithms, such as Adaptive Median filter (AMF), These algorithms first detect the noisy pixels and remove it by applying either standard median filter or its variants. These filters are effective in removing low to medium density impulse noise only.

1. Less effective in removing Gaussian or random-intensity noise. The median filter can remove noise only if the noisy pixels occupy less than one half of the neighborhood area.
2. Repeating will remove noise but at the expense of detail (posterization occurs) where pixel brightness values are leveled across regions "group of pixels having similar brightness values
3. High computational cost (for sorting N pixels, the temporal complexity is $O(N \cdot \log N)$, When the median filter must be carried out in real time, the software implementation in general-purpose processors does not usually give good results and FPGAs are a good alternative
4. Some median algorithms are not good for real time processing.

5. The median filter gives brightness differences resulting in maximal blurring of regional boundaries.
6. Median computer algorithm cannot be customized.

1.5 Impulse Detection

In an image contaminated by random-valued impulse noise, the detection of noisy pixel is more difficult in comparison with fixed valued impulse noise, as the gray value of noisy pixel may not be substantially larger or smaller than those of its neighbors. Due to this reason, the conventional median-based impulse detection methods do not perform well in case of random valued impulse noise. In order to overcome this problem, we use a non linear function to transform the pixel values within the filter window $W(x) (i, j)$ in a progressive manner. This operation widens the gap between noisy pixel $x (i,j)$ and the other pixels in the window $W(x) (i, j)$. In the beginning of each iteration, the central pixel $x (i,j)$ of each window is subtracted from all the pixels in the window and normalized absolute differences are obtained

$$d(m,n) = |x(m,n) - x(i,j)| / 255; x(m,n) \in W^{(x)}(i,j) \dots\dots 2$$

The normalized absolute differences, are then transformed by a nonlinear function to increase the gap between the differences $d(m, n)$ corresponding to noisy pixels and those due to noise-free Pixels

$$d^{(t)}(m,n) = e^{K \cdot d(m,n)} - 1;$$

$$m = i - L, \dots, i + L, n = j - L, \dots, j + L$$

where $d^{(t)}(m, n)$ denotes the transformed value of $d(m, n)$ and K is a constant which varies with iterations. The transformed values $d^{(t)}(m, n)$ are sorted as $\{d^{(t)}(1) \leq d^{(t)}(2) \leq \dots \leq d^{(t)}(9)\}$ in ascending order where $\{d^{(t)}(1), d^{(t)}(2), \dots, d^{(t)}(9)\}$ are the transformed values $\{d(m, n)\}$ of . Now, the central pixel is considered noisy for a filtering window of size 3×3 if . The output of the detector is represented by a binary flag image $\{f(i, j)\}$, where $f(i, j) = 1$ indicates that the pixel $x(i, j)$ is noisy; for noiseless pixel, $f(i, j) = 0$.

CHAPTER 2

LITERATURE SURVEY

An Efficient Hybrid Fuzzy-Clustering Driven 3D-Modeling of Magnetic Resonance Imagery for Enhanced Brain Tumor Diagnosis, IEEE 2019

Suresh Kanniappan, Duraimurugan Samiayya

Mind tumor discovery and its investigation are fundamental in clinical conclusion. The proposed work centers around fragmenting anomaly of hub mind MR DICOM cuts, as this configuration holds the upside of rationing broad metadata. The hub cuts assume the left and right piece of the cerebrum is symmetric by a Line of Symmetry (LOS). A semi-mechanized framework is intended to mine typical and strange designs from each mind MR cut in a DICOM study. In this work, Fuzzy bunching (FC) is applied to the DICOM cuts to extricate different groups for various k . At that point, the best-fragmented picture that has high between class unbending nature is acquired utilizing the outline wellness work. The grouped limits of the tissue classes additionally upgraded by morphological activities. The FC method is hybridized with the standard picture post-preparing strategies, for example, marker controlled watershed division (MCW), locale developing (RG), and distance regularized level sets (DRLS). This methodology is executed on eminent BRATS challenge dataset of various modalities and a clinical dataset containing hub T2 weighted MR pictures of a patient. The consecutive investigation of the cuts is performed utilizing the metadata data present in the DICOM header. The approval of the division techniques against the ground truth pictures approves that the fragmented objects of DRLS through FC upgraded mind pictures accomplish most extreme scores of Jaccard and Dice comparability coefficients. The normal Jaccard and dice scores for portioning tumor part for ten patient investigations of the BRATS dataset are 0.79 and 0.88, likewise for the clinical examination 0.78 and 0.86, individually. At long last, 3D perception and tumor volume assessment are finished utilizing available DICOM data.

MR Brain Image Segmentation: A Framework to Compare Different Clustering Techniques, IEEE 2019

Laura Caponetti ^{1,†}, Giovanna Castellano

In Magnetic Resonance (MR) mind picture examination, division is generally utilized for recognizing, estimating and breaking down the fundamental anatomical constructions of the cerebrum and in the end distinguishing neurotic areas. Mind

picture division is of basic significance since it helps clinicians and specialists to focus on explicit districts of the cerebrum to break down them. Be that as it may, division of mind pictures is a troublesome errand because of high similitudes and connections of power among various locales of the cerebrum picture. Among different strategies proposed in the writing, grouping calculations end up being fruitful devices for picture division. In this paper, we present a structure for picture division that is given to help the master in distinguishing diverse cerebrum areas for additional investigation. The structure incorporates diverse bunching techniques to perform division of MR pictures. Moreover, it empowers simple examination of various division results by giving a quantitative assessment utilizing an entropy-based measure just as different measures ordinarily used to assess division results. To show the capability of the structure, the executed bunching techniques are looked at on reenacted T1-weighted MR mind pictures from the Internet Brain Segmentation Repository (IBSR data set) furnished with ground truth division.

New Method of Classification to Detect Alzheimer Disease, IEEE 2019

Amira Ben Rabeh; Faouzi Benzarti; Hamid Amiri

This paper presents another technique for grouping to identify Alzheimer Disease in any progression: Early controls, Mild Cognitive Impairment (MCI) and Alzheimer Disease (AD). In this paper, we will introduce our strategy for grouping, which depends on the aftereffects of the technique for division Level Set. The achievement of such a characterization strategy is because of the division technique and the extraction of the region to be considered. Additionally, the descriptors utilized while removing the structure to give us better order results. We will introduce our administered grouping technique. The strategy comprises in considering the 4 learning tests whose passage is nearest to the new section X, as per four distances: Euclidean, Manhattan, Hausdorff, AMED (Average Minimum Euclidean Distance). Base to appraise the yield related with another information X. We tried our CAD with 75 subjects: 25 Normal (age $\pm$ SD=60 $\pm$ 8 years), 25 MCI (age $\pm$ SD=65 $\pm$ 8 years) and 25 Alzheimer (age $\pm$ SD=60 $\pm$ 8 years). The strategy demonstrated an exactness of 92% at Alzheimer Disease recognition. Our technique can be a valuable device to analyze Alzheimer Diseases in any Step.

A division procedure to distinguish the Alzheimer's infection utilizing picture preparing, IEEE 2020

R. Anitha; Prakash; S. Jyothi

Alzheimer's illness is a neurological issue wherein the demise of synapses causes cognitive decline and intellectual decay. A neurodegenerative sort of dementia, the infection begins gentle and deteriorates. A significant territory under clinical examination is Brain picture investigation, results to distinguish mind illnesses. The primary driver for Alzheimer's illnesses is low mind movement and blood stream. Overall Segmentation procedure is utilizing for the clinical pictures. One of the significant segment of the cerebrum is Hippocampus. The ordinary conduct of individuals is relies upon the usefulness of Hippocampus. Manual Segmentation by an expert on the Hippocampus requires numerous hours. In picture handling there are different procedures accessible for division measure. In this paper an altered methodology dependent on the watershed calculation is utilized for sectioning the hippocampus district. The mind pictures changed over into parallel structure utilizing two methodologies. The principal approach is block mean, cover and marking ideas and in the subsequent methodology formal hat, veil and naming ideas. Anyway it is tracked down that some piece of the picture contains openings which intrude on the division interaction. To defeat this issue picture opening filling methods are executed and related parts are assembled into associated segments. The shape investigation of hippocampus construction will bring about characterizing the Alzheimer's sickness.

Completely programmed mind division for Alzheimer's infection discovery from attractive reverberation pictures, IEEE 2020

Chaturaphat Tanchi; Nipon Theera-Umpon; Sansanee Auephanwiriyakul

This paper proposes another programmed strategy to section the entire cerebrum in attractive reverberation (MR) picture arrangement and ascertain its volume for recognizing Alzheimer's sickness (AD). The hidden MR pictures were gotten from the Alzheimer's Disease Neuroimaging Initiative (ADNI) information base. The entire mind T1-weighted MRI was performed at 1.5 T in 100 subjects. The proposed programmed division strategy depends on the numerical morphology of picture and our proposed procedure called the "cerebrum format" to restrict the limit around the mind. The outcomes show that the volumes of AD patients, gentle psychological impedance (MCI) patients, and ordinary people are $828 \pm 49 \text{ mm}^3$, $922 \pm 30 \text{ mm}^3$, and $1056 \pm 102 \text{ mm}^3$, individually. We likewise played out the three-class characterization issue on the informational index utilizing the Bayes classifier and four-crease cross approval. The order pace of 87% is accomplished on the test sets.

PC Aided Diagnosis System for Alzheimer's Disease Using Fuzzy-Possibilistic Tissue Segmentation and SVM Classification, IEEE 2020

Lilia Lazli; Mounir Boukadoum; Otmame Ait Mohamed

We portray a PC helped analysis (CAD) framework for segregating patients experiencing Alzheimer's illness (AD) dementia and sound patients. It depends on: 1) a grouping cycle to survey white matter, dim matter and cerebrospinal liquid volumes from loud anatomical attractive reverberation (MR) and practical positron discharge tomography (PET) mind pictures 1 1The MR and PET information utilized in this work were gotten from the Alzheimer's sickness Neuroimaging Initiative (ADNI) data set (<http://adni.loni.usc.edu/>); 2) an arrangement interaction that recognizes the cerebrum pictures of typical and AD patients. The grouping stage comprises of three stages: First, the fluffy c-implies (FCM) calculation is utilized for a fluffy segment of the underlying class centroids. Second, fluffy tissue maps are registered utilizing a possibilistic C-implies (PCM) calculation that utilizes the FCM parcel to acquire the last picture bunches. The last division is then made to delimit the mind tissue volumes. For the arrangement stage, a help vector machine (SVM) is utilized with various bit capacities. Approving the proposed CAD framework on the MRI and PET pictures of 45 AD and 50 solid cerebrums, of subjects matured somewhere in the range of 55 and 90 years, shows better affectability, particularity and exactness in contrast with three elective methodologies, specifically FCM, PCM and VAF (Voxels-As-Features). The precision rates for the noisiest pictures (20% of commotion) were 75% for MRI and 73% for PET output, contrasted with 71 % and 70,2%, 68.5% and 67%, and 65 % and 64.7 % with the three different methodologies, separately.

Towards Alzheimer's sickness grouping through move learning, IEEE 2020

Marcia Hon; Naimul Mefraz Khan

Identification of Alzheimer's Disease (AD) from neuroimaging information, for example, MRI through AI have been a subject of exceptional examination as of late. Ongoing accomplishment of profound learning in PC vision have advanced such examination further. Nonetheless, basic limits with such calculations are dependence on an enormous number of preparing pictures, and prerequisite of cautious improvement of the design of profound organizations. In this paper, we endeavor tackling these issues with move realizing, where cutting edge models, for example, VGG and Inception are introduced with pre-prepared loads from huge benchmark datasets comprising of normal pictures, and the completely associated layer is re-prepared with just few MRI pictures. We utilize picture

CHAPTER 3

SYSTEM MODEL

3.1 SEGMENTATION

Image segmentation become, is and may be a main studies subject matter for plenty photograph processing researchers. The motives are apparent and packages endless: maximum pc imaginative and prescient and photograph evaluation issues require a segmentation level so that you can discover gadgets or divide the photograph into areas which may be taken into consideration homogeneous in keeping with a given criterion, including colour, motion, texture, etc. Clustering is the look for awesome agencies withinside the function area. It is predicted that those agencies have specific systems and that may be truly differentiated. The clustering challenge separates the information into wide variety of walls, that are volumes withinside the n-dimensional function area. These walls outline a difficult restriction among the specific agencies and depend upon the features used to version the information distribution.

3.1.1 Image segmentation:

- To human beings, an photograph isn't only a random series of pixels; it's far a significant association of areas and gadgets. There additionally exists loads of pix: herbal scenes, paintings, etc. Despite the massive versions of those pix, human beings haven't any trouble to interpret them. Considering the massive databases at the WWW, in our private photo folders, a sturdy and automated photograph evaluation might be welcome. Image segmentation is step one in photograph evaluation and sample recognition. It is an important and crucial element of photograph evaluation system, is one of the maximum hard duties in photograph processing, and determines the first-class of the very last end result of evaluation. Image segmentation is the system of dividing an photograph into specific areas such that every place is homogeneous.

Image segmentation strategies may be labeled as follows (this isn't an exhaustive list):

- **Histogram thresholding:** assumes that pix are composed of areas with specific gray (or colour) ranges, and separates it into some of peaks, every similar to one place.
- **Edge-based approaches:** use facet detection operators including Sobel, Laplacian for example. Resulting areas might not be connected, therefore edges want to be joined.
- **Region-based approaches:** : primarily based totally on similarity of nearby photograph information. Some of the extra extensively used methods on this class are: Thresholding, Clustering, Region growing, Splitting and merging..
- **Hybrid:** take into account each edges and areas.

The task is accomplished the use of Image Segmentation with the aid of using Clustering. It is primarily based totally on Color photograph segmentation the use of Mahalanobis distance. Euclidean distance is likewise used for evaluating among the first-class of segmentation among the Mahalanobis and Euclidean distance.

a)Image Segmentation by Clustering

Clustering is a class method. Given a vector of N measurements describing every pixel or institution of pixels (i.e., place) in an photograph, a similarity of the dimension vectors and consequently their clustering withinside the N-dimensional dimension area implies similarity of the corresponding pixels or pixel agencies. Therefore, clustering in dimension area can be a trademark of similarity of photograph areas, and can be used for segmentation purposes.

The vector of measurements describes a few beneficial photograph function and accordingly is likewise called a function vector. Similarity among photograph areas or pixels implies clustering (small separation distances) withinside the function area. Clustering strategies had been a number of the earliest information segmentation strategies to be advanced..

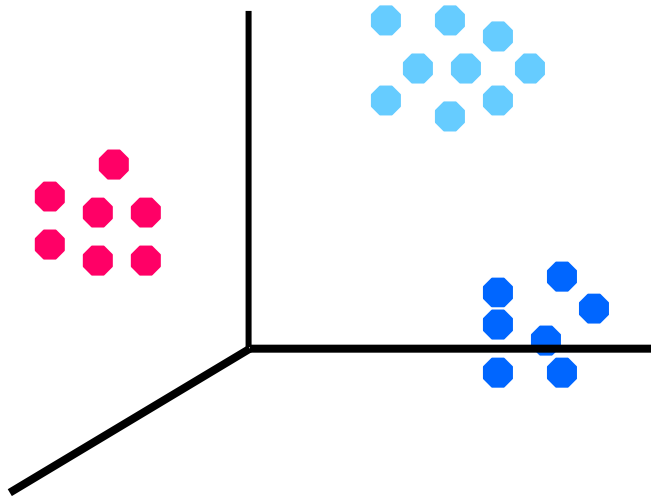


Fig. 3.1: Similarity between image regoins or pixels

Similar data points grouped together into clusters.

Most popular clustering algorithms suffer from two major drawbacks

First, the wide variety of clusters is predefined, which makes them insufficient for batch processing of massive photograph databases

Secondly, the clusters are represented with the aid of using their centroid and constructed the use of an Euclidean distance consequently inducing usually an hyperspheric cluster shape, which makes them not able to seize the actual shape of the information.

This is particularly authentic withinside the case of colour clustering in which clusters are arbitrarily fashioned

3.2 CLUSTERING ALGORITHMS:

- **K-means**
- **FCM**

There are many other algorithms used for clustering.

K-approach set of rules become used withinside the task and the distances had been calculated the use of Mahalanobis and Euclidean distances

K-Means Clustering Overview

K-Means clustering generates a particular wide variety of disjoint, flat (non-hierarchical) clusters. It is properly proper to producing globular clusters. The K-Means approach is numerical, unsupervised, non-deterministic and iterative.

K-Means Algorithm Properties

- There are usually K clusters.
- There is usually at the least one object in every cluster.
- The clusters are non-hierarchical and that they do now no longer overlap.
- Every member of a cluster is towards its cluster than another cluster due to the fact closeness does now no longer usually contain the middle of clusters.

The K-Means Algorithm Process

- The dataset is partitioned into K clusters and the information factors are randomly assigned to the clusters ensuing in clusters which have kind of the identical wide variety of information factors.

For every information factor:

- Calculate the distance (Mahalanobis or Euclidean) from the information factor to every cluster.
- If the information factor is closest to its very own cluster, go away it in which it's far. If the information factor isn't closest to its very own cluster, flow it into the nearest cluster.
- Repeat the above step till a whole by skip thru all of the information factors outcomes in no information factor transferring from one cluster to another. At this factor the clusters are solid and the clustering system ends.
- The preference of preliminary partition can significantly have an effect on the very last clusters that end result, in phrases of inter-cluster and intra-cluster distances and cohesion.

How the problem was approached?

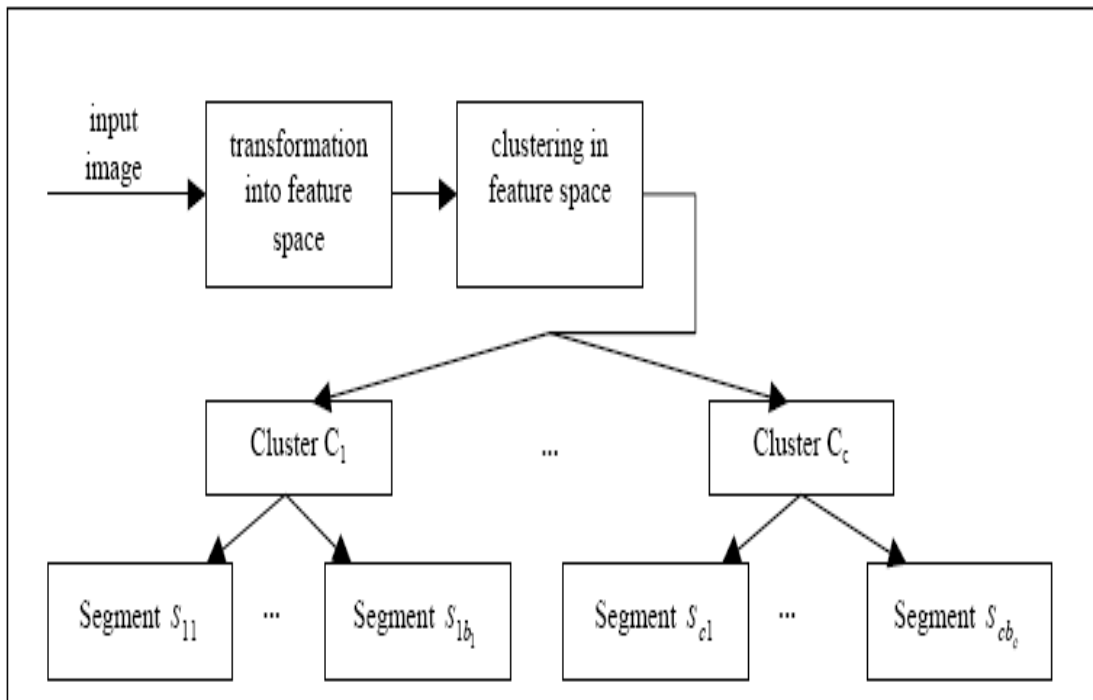


Fig. 3.2: Flow-chart of an image segmentation method

Step 1: First, an photograph is taken as an enter. The enter photograph is withinside the shape of pixels and is converted right into a function area (RBG).

Step 2: Next comparable information factors, i.e. the factors that have comparable colour, are grouped collectively the use of any clustering approach. A clustering approach including okay-approach clustering is used to shape clusters as proven withinside the glide chart. The distances are calculated the use of Mahalanobis and Euclidean distant.

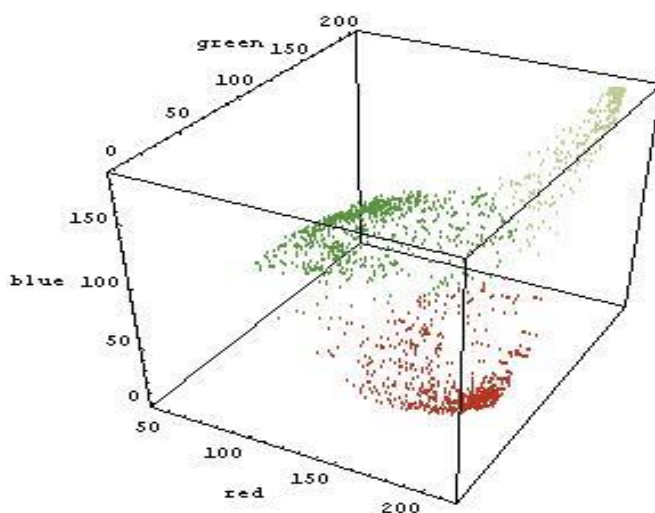


Fig. 3.3: K-means clustering method

The above determine indicates how the information factors are clustered within the three-d RGB area. As it is easy to see all comparable colorations are grouped collectively to shape a cluster. The information factors with minimal Mahalanobis distance or Euclidean distance are grouped collectively to shape the clusters. Mahalanobis and Euclidean are defined later below.

Step 3: After clustering is accomplished, the imply of the clusters is taken. Then the imply colour in every cluster is calculated to be remapped onto the photograph.

Cluster analysis

Clustering is the class of gadgets into specific agencies, or extra precisely, the partitioning of a information set into subsets (clusters), in order that the information in every subset (ideally) proportion a few not unusualplace trait - regularly proximity in keeping with a few described distance measure. Data clustering is a not unusualplace method for statistical information evaluation, that is used in lots of fields, consisting of system learning, information mining, sample recognition, photograph evaluation and bioinformatics. The computational challenge of classifying the information set into okay clusters is regularly called okay-clustering. Besides the time period information clustering (or simply clustering), there are some of phrases with comparable meanings, consisting of cluster evaluation, automated class, numerical taxonomy, botryology and typological evaluation.

3.3 K MEANS SEGMENTATION

Introduction

Both of the algorithms beneath attention date lower back at first over 30 years. A K-Means set of rules become delivered with the aid of using call in 1967 even as an EM set of rules become relatively formalized ten years later in 1977. The dates connected to those algorithms may be relatively puzzling because the EM set of rules may be taken into consideration a generalized K-Means set of rules. It is secure to expect that each algorithms existed formerly with out formalization or a whole clarification of the concept involved. In order to recognize the way to enforce every set of rules, the elegance notes and Wikipedia had been depended on heavily. In

addition, some of the papers located within the references phase had been of restricted assistance.

The K-Means set of rules and the EM set of rules can each be used to discover herbal clusters inside given information primarily based totally upon various enter parameters. Clusters may be fashioned for pix primarily based totally on pixel depth, colour, texture, location, or a few aggregate of those. For each algorithms the beginning places of the walls used are very essential and might make the distinction among an most effective and a non-most effective answer on the grounds that each are vulnerable to termination while accomplishing a nearby most in preference to the worldwide most. K-Means may be idea of as an set of rules counting on difficult mission of statistics to a given set of walls. At each byskip of the set of rules, every information price is assigned to the closest partition primarily based totally upon a few similarity parameter including Euclidean distance of depth. The walls are then recalculated primarily based totally on those difficult assignments. With every successive byskip, a information price can transfer walls, accordingly changing the values of the walls at each byskip. K-Means algorithms normally converge to an answer right away in preference to different clustering algorithms.

3.3.1 Methodology

Two K-Means algorithms were implemented. The first clusters the pixel statistics from an enter photograph primarily based totally at the RGB colour of every pixel, and the second one clusters primarily based totally on pixel depth. The set of rules starts with the introduction of preliminary walls for the information. The clustering primarily based totally on pixel colour may be taken into consideration first.

In order to attempt to enhance the runtime and outcomes of the set of rules, walls that are similarly spaced had been selected. Initially, 8 walls had been selected. The walls represented red, green, blue, white, black, yellow, magenta, and cyan or the corners of the “colour cube”. With the preliminary walls selected, the set of rules can begin. Every pixel within the enter photograph is in comparison in opposition to the preliminary walls and the closest partition is selected and recorded. Then, the imply in phrases of RGB colour of all pixels inside a given partition is determined. This imply is then used as the brand new price for the given partition. If a partition has no pixels related to it, it stays unchanged. In a few implementations, a partition without a pixels related to it'd be removed; however, those walls are actually neglected on this implementation. Once the brand new partition values were determined, the set of rules returns to assigning every pixel to the closest partition. The set of rules maintains till pixels are not converting which partition they're related to or, as is the case here, till

not one of the partition values modifications with the aid of using extra than a hard and fast small amount. In order to acquire extra outcomes, the preliminary walls used had been numerous with the aid of using including and casting off walls. In a almost equal setup, a 2nd K-Means implementation become made the use of the grayscale depth of every pixel in place of the RGB colour to partition the photograph. The beginning walls had been selected as similarly spaced values from zero to 255. The wide variety of walls used, as withinside the colour segmenting setup, become numerous so that you can growth the wide variety of outcomes to be had and to have a look at the consequences of various this parameter.

For this case, the identical preliminary walls as used withinside the colour segmentation with K-Means had been used so that you can make the evaluation of outcomes extra significant. Here, RGB colour become once more selected because the evaluation parameter.

$$E[z_{ij}] = \frac{p(x = x_i | \mu = \mu_j)}{\sum_{n=1}^k \frac{p(x = x_i | \mu = \mu_n)}{e^{\frac{1}{2\sigma^2}(x_i - \mu_n)^2}}} = \frac{p(x = x_i | \mu = \mu_j)}{\sum_{n=1}^k e^{-\frac{1}{2\sigma^2}(x_i - \mu_n)^2}}$$

This equation states that the expectancies or weight for pixel z with admire to partition j equals the opportunity that x is pixel xi for the reason that μ is partition μ_i divided with the aid of using the sum over all walls okay of the identical formerly defined opportunity. This ends in the decrease expression for the weights. The sigma squared visible withinside the 2nd expression represents the covariance of the pixel information. Once the E step has been accomplished and each pixel has a weight or expectation for every partition, the M step or maximization step starts. This step is described with the aid of using the subsequent equation:

$$\mu_j \leftarrow \frac{1}{m} \sum_{i=1}^m E[z_{ij}] x_i$$

This equation states that the partition price j is modified to the weighted common of the pixel values in which the weights are the weights from the E step for this precise

partition. This EM cycle is repeated for every new set of walls till, as withinside the K-Means set of rules, the partition values not alternate with the aid of using a large amount.

Medical imaging refers back to the strategies and tactics used to create pix of the human body (or components thereof) for medical purposes (scientific tactics in search of to reveal, diagnose or take a look at disease) or scientific science (consisting of the have a look at of regular anatomy and function).

As a area and in its widest sense, it's far a part of organic imaging and includes radiology (withinside the wider sense), radiological sciences, endoscopy, (scientific) thermography, scientific pictures and microscopy (e.g. for human pathological investigations). Measurement and recording strategies which aren't typically designed to provide pix, including electroencephalography (EEG) and magnetoencephalography (MEG) and others, however which produce information vulnerable to be represented as maps (i.e. containing positional statistics), may be visible as types of scientific imaging. In the medical context, scientific imaging is usually equated to radiology or "medical imaging" and the scientific practitioner liable for interpreting (and now and again obtaining) the pix are a radiologist. Diagnostic radiography designates the technical factors of scientific imaging and especially the purchase of scientific pix. The radiographer or radiologic technologist is typically liable for obtaining scientific pix of diagnostic first-class, despite the fact that a few radiological interventions are accomplished with the aid of using radiologists.

As a area of clinical investigation, scientific imaging constitutes a sub-area of biomedical engineering, scientific physics or medication relying at the context: Research and improvement withinside the vicinity of instrumentation, photograph acquisition (e.g. radiography), modeling and quantification are typically the keep of biomedical engineering, scientific physics and pc science; Research into the software and interpretation of scientific pix is typically the keep of radiology and the scientific sub-area applicable to scientific circumstance or vicinity of scientific science (neuroscience, cardiology, psychiatry, psychology, etc) beneathneath investigation. Many of the strategies advanced for scientific imaging additionally have clinical and commercial packages.

Medical imaging is regularly looked as if it would designate the set of strategies that noninvasively produce pix of the inner issue of the body. In this confined sense, scientific imaging may be visible as the answer of mathematical inverse issues. This approach that cause (the residences of residing tissue) is inferred from effect (the determined signal). In the case of ultrasonography the probe includes ultrasonic strain waves and echoes withinside the tissue display the inner shape. In the case of

projection radiography, the probe is X-ray radiation that is absorbed at specific fees in specific tissue sorts including bone, muscle and fat.

The K-approach set of rules is an iterative method this is used to partition an photograph into K clusters. The K-approach set of rules assigns every factor to the cluster whose middle (additionally referred to as centroid) is nearest. The middle is the common of all of the factors withinside the cluster — this is, its coordinates are the mathematics imply for every measurement one at a time over all of the factors withinside the cluster. Example: The information set has 3 dimensions and the cluster has factors: $X = (x_1, x_2, x_3)$ and $Y = (y_1, y_2, y_3)$. Then the centroid Z will become $Z = (z_1, z_2, z_3)$, in which $z_1 = (x_1 + y_1)/2$ and $z_2 = (x_2 + y_2)/2$ and $z_3 = (x_3 + y_3)/2$.

The set of rules steps are :

- 1-Choose the wide variety of clusters, okay.
- 2-Randomly generate okay clusters and decide the cluster centers, or immediately generate okay random factors as cluster centers.
- 3-Assign every factor to the closest cluster middle.
- 4-Recompute the brand new cluster centers.
- 5-Repeat the 2 preceding steps till a few convergence criterion is met (typically that the mission hasn't changed).

The important benefits of this set of rules are its simplicity and velocity which permits it to run on massive datasets.

Its drawback is that it does now no longer yield the identical end result with every run, because the ensuing clusters depend upon the preliminary random assignments.

It minimizes intra-cluster variance, however does now no longer make certain that the end result has a international minimal of variance.

3.3.2 k-means algorithm

K-approach set of rules The okay-approach set of rules is an set of rules to cluster n gadgets primarily based totally on attributes into okay walls, okay be a set of Q feature vectors. Each feature vector $x(q) = (x_1(q), \dots, x_N(q))$ has N components. The process of clustering is to assign the Q feature vectors into K clusters usually by the minimum distance assignment principle.

$$V = \sum_{i=1}^k \sum_{x_j \in S_i} (x_j - \mu_i)^2$$

where there are k clusters S_i , $i = 1, 2, \dots, k$, and μ_i is the [centroid](#) or mean point of all the points $x_j \in S_i$.

The most common form of the algorithm uses an iterative refinement heuristic known as [Lloyd's algorithm](#). Lloyd's algorithm starts by partitioning the input points into k initial sets, either at random or using some heuristic data. It then calculates the mean point, or centroid, of each set. It constructs a new partition by associating each point with the closest centroid. Then the centroids are recalculated for the new clusters, and algorithm repeated by alternate application of these two steps until convergence, which is obtained when the points no longer switch clusters (or alternatively centroids are no longer changed).

Lloyd's algorithm and k-means are often used synonymously, but in reality Lloyd's algorithm is a heuristic for solving the k-means problem, but with certain combinations of starting points and centroids, Lloyd's algorithm can in fact converge to the wrong answer (ie a different and optimal answer to the minimization function above exists.)

Other variations exist, but Lloyd's algorithm has remained popular because it converges extremely quickly in practice. In fact, many have observed that the number of iterations is typically much less than the number of points. Recently, however, David Arthur and Sergei Vassilvitskii showed that there exist certain point sets on which k-means takes [superpolynomial time](#): $2^{\Omega(\sqrt{n})}$ to converge.

Approximate k-means algorithms have been designed that make use of [coresets](#): small subsets of the original data.

In terms of performance the algorithm is not guaranteed to return a global optimum. The quality of the final solution depends largely on the initial set of clusters, and may, in practice, be much poorer than the global optimum. Since the algorithm is extremely

fast, a common method is to run the algorithm several times and return the best clustering found.

A drawback of the k-means algorithm is that the number of clusters k is an input parameter. An inappropriate choice of k may yield poor results. The algorithm also assumes that the [variance](#) is an appropriate measure of cluster scatter.

Demonstration of the algorithm

The following images demonstrate the k-means clustering algorithm in action, for the two-dimensional case. The initial centres are generated randomly to demonstrate the stages in more detail.

Applications of the algorithm

Image Segmentation

The k-means clustering algorithm is commonly used in [computer vision](#) as a form of [image segmentation](#). The results of the segmentation are used to aid [border detection](#) and [object recognition](#). In this context, the standard [euclidean distance](#) is usually insufficient in forming the clusters. Instead, a weighted distance measure utilizing [pixel](#) coordinates, [RGB](#) pixel color and/or intensity, and image texture is commonly used.

Model of fuzzy c-mean method (FCM)

The standard FCM is an iterative, unsupervised clustering algorithm, initially developed by FCM algorithm, introduced. The following model of FCM is described.

The Observed MRI signal is modeled as a product of the true signal generated by the underlying anatomy, and a spatially varying factor called the gain field

$$Y_k = X_k G_k \quad \forall k \in \{1, 2, \dots, N\} \quad (1)$$

groups the values X_k , Y_k and G_k are the true intensity, observed intensity and the gain field at the k th voxel, respectively. N is the total number of pixels in the MRI volume.

The application of a logarithmic transformation to the intensities allows the artifact to be modeled as an additive bias field

$$y_k = x_k + \beta_k \quad \forall k \in \{1, 2, \dots, N\} \quad (2)$$

where x_k and y_k are the true and observed log-transformed intensities at the k th voxel, respectively, and β_k is the bias field at the k th voxel. If the gain field is known, then it is relatively easy to estimate the tissue class by applying a conventional intensity-based segmentation to the corrected data. The following discussion is based the model of (2) and estimation of the gain field β_k .

Modified FCM algorithm(M-FCM)

In the followings, we will introduce some modifications to this algorithm. The evaluation of the method for localized measurements, such as the impact on Alzheimer boundary or volume determinations also needs further work.

$$J_m = \sum_{i=1}^c \sum_{k=1}^N u_{ik}^p \|y_k - \beta_k - v_i\|^2 + \sum_{i=1}^c \sum_{k=1}^N u_{ik}^p \left(\sum_{y_r \in N_k} w(y_k, y_r) \|y_r - \beta_r - v_i\|^2 \right) \quad (3)$$

Where $w(y_k, y_r)$ is a weighting function, satisfied the following conditions

$$\sum_{y_r \in N_k} w(y_k, y_r) = \alpha, \quad 0 \leq \alpha < 1, \quad \forall k \in \{1, 2, \dots, N\}$$

especially, when $w(y_k, y_r) = \frac{\alpha}{N_R}$, the J_m is BCFCM objective function(3) proposed.

Formally, the optimization problem is estimated those parameters in the form

$$\min_{u_{i,k}, v_i, \beta_k} J_m \quad (4)$$

The objective function can be calculated as the BCFCM algorithm. Taking the first derivatives of J_m with respect to u_{ik}, v_i, β_k , and setting them to zero results in three necessary but not sufficient conditions for J_m to be at a local maximum. In the following sections, we derive these estimating results and propose the algorithm..

A. Membership Evaluation

$$u_{ik}^* = \frac{1}{\sum_{j=1}^c \left(\frac{D_{ik} + \gamma_{ik}}{D_{ij} + \gamma_{ij}} \right)^{1/(p-1)}} \quad (5)$$

where $D_{ik} = \|y_k - \beta_k - v_i\|^2$, and $\gamma_{ik} = \sum_{y_r \in N_k} w(y_k, y_r) \|y_r - \beta_r - v_i\|^2$

B. Cluster Prototype Updating

$$v_i^* = \frac{\sum_{k=1}^N u_{ki}^p \left((y_k - \beta_k) + \sum_{y_r \in N_k} w(y_k, y_r) (y_r - \beta_r) \right)}{\sum_{k=1}^N u_{ki}^p (1 + \sum_{y_r \in N_k} w(y_k, y_r))} \quad (6)$$

C. Bias-Field Estimation

$$\beta_k^* = y_k - \frac{\sum_{i=1}^c v_i \left(u_{ik}^p + \sum_{y_r \in N_k} w(y_k, y_r) u_{ir}^p \right)}{\sum_{i=1}^c \left(u_{ik}^p + \sum_{y_r \in N_k} w(y_k, y_r) u_{ir}^p \right)} \quad (7)$$

D. The discuss of the convergence

Theory: if $w(y_k, y_r) \geq 0$ and

$$\sum_{y_r \in N_k} w(y_k, y_r) = \alpha, \quad 0 \leq \alpha < 1, \quad \forall k \in \{1, 2, \dots, N\} \text{ and } N_k \text{ is a 4 or 8 - connective}$$

neighbourhood.

Then objective function J_m is convergence.

E. M-FCM Algorithm

The M-FCM algorithm for correcting the bias field and segmenting the image into different clusters can be summarized in the following steps.

Step 1: Select the Weighting function, in general,

$$w(y_k - y_r) = \alpha e^{-\frac{\|y_k - y_r\|^2}{\sigma^2}} \quad (8)$$

where $0 \leq \alpha < 1, \sigma \geq 1$;

Step 2: Select initial class prototypes $\{v_i\}_{i=1}^c$, for example

$$\left\{v_i = \log(255 * (2i-1) / 2c)\right\}_{i=1}^c$$

Set $\{\beta_k\}_{k=1}^N$ to equal and very small values (e.g., 0.01).

Step 3: Update the partition matrix using (5).

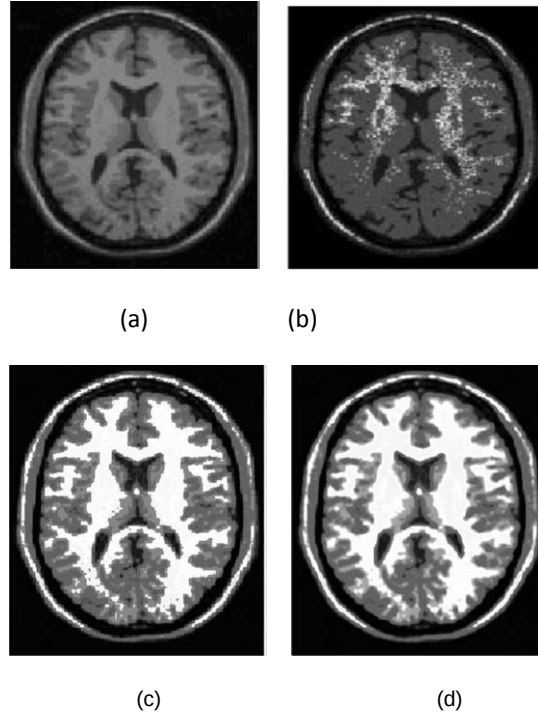
Step 4: The prototypes of the clusters are obtained in the form of weighted averages of the patterns using (6).

Step 5: Estimate the bias term using (7).

Repeat Steps 3)–5) till termination. The termination criterion is as follows:

$$\|V_{new} - V_{old}\| < \varepsilon \quad (9)$$

where $\|\cdot\|$ is the Euclidean norm, V is a vector of cluster centres, and ε is a small number that can be set by the user (e.g., 0.01). We describe the application of the M-FCM segmentation on synthetic images corrupted with multiplicative gain and real T1 brain MR images. Simulating image is a T1-weighted phantom with in-plane high resolution, Gaussian noise with 6.0, and three-dimensional linear shading 7% in each direction. There are many advantages for using digital phantoms rather than real image including in prior knowledge of the true tissue types and control over image parameters such as mean intensity values, noise and intensity in homogeneities. We also employed the fast algorithm improving calculation effect, because its consumed time is 1/4 of the traditional algorithm.



$$TR(A) = \frac{\text{number} \{x \mid x \in A \subset WM\}}{\text{number} \{x \subset WM\}} \times 100\% \quad (10)$$

Fig. 3.4: M-FCM Segmentation on synthetic images corrupted with multiplicative gain and real T1 brain MRI images

Clustering is the process of grouping feature vectors into classes in the self-organizing mode. Let $\{\mathbf{x}^{(q)}: q = 1, \dots, Q\}$ be a set of Q feature vectors. Each feature vector $\mathbf{x}^{(q)} = (x_1^{(q)}, \dots, x_N^{(q)})$ has N components. The process of clustering is to assign the Q feature vectors into K clusters $\{\mathbf{c}^{(k)}: k = 1, \dots, K\}$ usually by the minimum distance assignment principle.

Choosing the representation of cluster centers (or prototypes) is crucial to the clustering. Feature vectors that are farther away from the cluster center should not have as much weight as those that are close. These more distant feature vectors are outliers usually caused by errors in one or more measurements or a deviation in the processes that formed the object.

The simplest weighting method is arithmetic averaging. It adds all feature vectors in a cluster and takes the average as prototype. Because of its simplicity, it is still widely used in the clustering initialization.

The arithmetic averaging gives the central located feature vectors the same weights as outliers. To lower the influence of the outliers, median vectors are used in some proposed algorithms. To be more immune to outliers and more representative, the fuzzy weighted average is introduced to represent prototypes:

$$\mathbf{Z}_n^{(k)} = \sum_{\{q: q \in k\}} w_{qk} \mathbf{x}_n^{(q)}; \quad (1)$$

Rather than a Boolean value 1 (true, which means it belongs to the cluster) or 0 (false, does not belong), the weight w_{qk} in equation (1) represent partial membership to a cluster. It is called a fuzzy weight. There are different means to generate fuzzy weights.

One way of generating fuzzy weights is the reciprocal of distance

$$w_{qk} = 1 / D_{qk}, \quad (w_{qk} = 1 \text{ if } D_{qk} = 0) \quad (2)$$

It was used in earlier fuzzy clustering algorithms. When the distance between the feature vector and the prototype is large, the weight is small.

On the other hand, it is large when the distance is small. Using Gaussian functions to generate fuzzy weights is the most natural way for clustering. It is not only immune to outliers but also provides appropriate weighting for more centrally and densely

located vectors. It is used in the fuzzy clustering and fuzzy merging (FCFM) algorithm.

In this project, we implemented the fuzzy c-means (FCM) algorithm and the fuzzy clustering and merging algorithm in Java, applied the algorithms to several data sets and compared the weights of the two algorithms.

The segmentation of imaging data involves partitioning the image space into different cluster regions with similar intensity image values. The most medical images always present overlapping gray-scale intensities for different tissues. Therefore, Modified fuzzy clustering methods are particularly suitable for the segmentation of medical images. There are several Modified FCM clustering applications in the MRI segmentation of the brain. The Modified Fuzzy c-means (FCM) can be seen as the fuzzified version of the k-means algorithm. It is a method of clustering which allows one piece of data to belong to two or more clusters. This method is frequently used in pattern recognition. The algorithm is an iterative clustering method that produces an optimal c partition by minimizing the weighted within group sum of squared error objective function.

3.4 ADVANTAGES OF PROPOSED SYSTEM

It is best for convergence of gradients of the image pixels.

It is the fastest algorithm when compared to the k means algorithm and Fuzzy C Means algorithm. The MFCM algorithm can have linear convergence and the speed is based on how many information is lost.

MFCM algorithm is applicable for RGB colour space images.

The convergence rate of MFCM algorithm is the convergence rate of the E-step. That is to say, if the maximum value in M-step can be easily obtained, the convergence rate will be very fast to converge. The exact segmentation of the Alzheimer of MRI is possible.

Image Segmentation using FCM algorithm

The standard FCM is an iterative, unsupervised clustering algorithm, initially developed by FCM algorithm, introduced by Bezdek. The following model of FCM is described by Ahmed.

The Observed MRI signal is modeled as a product of the true signal generated by the underlying anatomy, and a spatially varying factor called the gain field

$$Y_k = X_k G_k \quad \forall k \in \{1, 2, \dots, N\} \quad (1)$$

groups the values, and are the true intensity, observed intensity and the gain field at the k th voxel, respectively. is the total number of pixels in the MRI volume.

The application of a logarithmic transformation to the intensities allows the artifact to be modeled as an additive bias field

$$y_k = x_k + \beta_k \quad \forall k \in \{1, 2, \dots, N\} \quad (2)$$

where x and y are the true and observed log-transformed intensities at the k th voxel, respectively, and is the bias field at the k th voxel. If the gain field is known, then it is relatively easy to estimate the tissue class by applying a conventional intensity-based segmentation to the corrected data. The following discussion is based the model of (2) and estimation of the gain field.

FCM algorithm (FCM)

In the followings, we will introduce some modifications to this algorithm. The evaluation of the method for localized measurements, such as the impact on Alzheimer boundary or volume determinations also needs further work.

$$J_m = \sum_{i=1}^c \sum_{k=1}^N u_{ik}^p \|y_k - \beta_k - v_i\|^2 + \sum_{i=1}^c \sum_{k=1}^N u_{ik}^p \left(\sum_{y_r \in N_k} w(y_k, y_r) \|y_r - \beta_r - v_i\|^2 \right) \quad (3)$$

Where $w(y_k, y_r)$ is a weighting function, satisfied the following conditions

$$\sum_{y_r \in N_k} w(y_k, y_r) = \alpha, \quad 0 \leq \alpha < 1, \quad \forall k \in \{1, 2, \dots, N\}$$

Formally, the optimization problem is estimated those parameters in the form

$$\min_{u_{i,k}, v_i, \beta_k} J_m \quad (4)$$

The objective function can be calculated as the BCFCM algorithm. Taking the first derivatives of with respect to ,, and setting them to zero results in three necessary but not sufficient conditions for to be at a local maximum. In the following sections, we derive these estimating results and propose the algorithm..

F. Membership Evaluation

$$u_{ik}^* = \frac{1}{\sum_{j=1}^c \left(\frac{D_{ik} + \gamma_{ik}}{D_{ij} + \gamma_{ij}} \right)^{1/(p-1)}} \quad (5)$$

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G. Cluster Prototype Updating

$$v_i^* = \frac{\sum_{k=1}^N u_{ki}^p \left((y_k - \beta_k) + \sum_{y_r \in N_k} w(y_k, y_r) (y_r - \beta_r) \right)}{\sum_{k=1}^N u_{ki}^p (1 + \sum_{y_r \in N_k} w(y_k, y_r))} \quad (6)$$

H. Bias-Field Estimation

$$\beta_k^* = y_k - \frac{\sum_{i=1}^c v_i \left(u_{ik}^p + \sum_{y_r \in N_k} w(y_k, y_r) u_{ir}^p \right)}{\sum_{i=1}^c \left(u_{ik}^p + \sum_{y_r \in N_k} w(y_k, y_r) u_{ir}^p \right)} \quad (7)$$

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$\sum_{y_r \in N_k} w(y_k, y_r) = \alpha$, $0 \leq \alpha < 1$, $\forall k \in \{1, 2, \dots, N\}$ and N_k is a 4 or 8 – connective neighborhood.

Then objective function J_m is convergence.

3.5 FCM Algorithm

The FCM algorithm for correcting the bias field and segmenting the image into different clusters can be summarized in the following steps.

Step 1: Select the Weighting function, in general,

$$w(y_k - y_r) = \alpha e^{-\frac{\|y_k - y_r\|^2}{\sigma^2}} \quad (8)$$

where $0 \leq \alpha < 1, \sigma \geq 1$;

Step 2: Select initial class prototypes,.

$$\left\{ v_i = \log(255 * (2i - 1) / 2c) \right\}_{i=1}^c$$

Set $\{\beta_k\}_{k=1}^N$ to equal and very small values (e.g., 0.01).

Step 3: Update the partition matrix using (5).

Step 4: The prototypes of the clusters are obtained in the form of weighted averages of the patterns using (6).

Step 5: Estimate the bias term using (7).

Repeat Steps 3)–5) till termination. The termination criterion is as follows:

$$\|V_{new} - V_{old}\| < \varepsilon \quad (9)$$

Where $\|\cdot\|$ is the Euclidean norm, V is a vector of cluster centers, and ε is a small number that can be set by the user (e.g., 0.01).

Fuzzy c Means clustered Image Segmentation

Introduction

Clustering is the process of grouping feature vectors into classes in the self-organizing mode. Let X be a set of Q feature vectors. Each feature vector $x(q) = (x_1(q), \dots, x_N(q))$ has N components. The process of clustering is to assign the Q feature vectors into K clusters usually by the minimum distance assignment principle.

Choosing the representation of cluster centers (or prototypes) is crucial to the clustering. Feature vectors that are farther away from the cluster center should not have as much weight as those that are close. These more distant feature vectors are outliers usually caused by errors in one or more measurements or a deviation in the processes that formed the object.

The simplest weighting method is arithmetic averaging. It adds all feature vectors in a cluster and takes the average as prototype. Because of its simplicity, it is still widely used in the clustering initialization.

The arithmetic averaging gives the central located feature vectors the same weights as outliers. To lower the influence of the outliers, median vectors are used in some proposed algorithms.

To be more immune to outliers and more representative, the fuzzy weighted average is introduced to represent prototypes:

$$Z_n^{(k)} = \sum_{\{q: q \in k\}} w_{qk} x_n^{(q)}; \quad (1)$$

Rather than a Boolean value 1 (true, which means it belongs to the cluster) or 0 (false, does not belong), the weight w_{qk} in equation (1) represent partial membership to a cluster. It is called a fuzzy weight. There are different means to generate fuzzy weights.

One way of generating fuzzy weights is the reciprocal of distance

$$w_{qk} = 1 / D_{qk}, \quad (w_{qk} = 1 \text{ if } D_{qk} = 0) \quad (2)$$

It was used in earlier fuzzy clustering algorithms. When the distance between the feature vector and the prototype is large, the weight is small. On the other hand, it is large when the distance is small. Using Gaussian functions to generate fuzzy weights is the most natural way for clustering. It is not only immune to outliers but also provides appropriate weighting for more centrally and densely located vectors. It is used in the fuzzy clustering and fuzzy merging (FCFM) algorithm.

In this project, we implemented the fuzzy c-means (FCM) algorithm and the fuzzy clustering and merging algorithm in Java, applied the algorithms to several data sets and compared the weights of the two algorithms.

Section 2 describes the background of clustering algorithms. Section 3 discusses the implementation of FCM algorithm and the results on data sets. Section 4 presents the results using the FCFM algorithm. Section 5 compares the fuzzy weights in FCM and the Gaussian weights in the FCFM algorithm.

Clustering Algorithms

The clustering groups a sample set of feature vectors into K clusters via an appropriate similarity (or dissimilarity) criterion (such as distance from the center of the cluster).

Fuzzy Clustering Algorithms

Fuzzy clustering plays an important role in solving problems in the areas of pattern recognition and fuzzy model identification. A variety of fuzzy clustering methods have been proposed and most of them are based upon distance criteria. One widely used algorithm is the fuzzy c-means (FCM) algorithm. It uses reciprocal distance to compute fuzzy weights. A more efficient algorithm is the new FCFM. It computes the cluster center using Gaussian weights, uses large initial prototypes, and adds processes of eliminating, clustering and merging. In the following sections we discuss and compare the FCM algorithm and FCFM algorithm.

3.6 The Fuzzy c-means Algorithm

The fuzzy c-means (FCM) algorithm was introduced by J. C. Bezdek. The idea of FCM is using the weights that minimize the total weighted mean-square error:

$$J(\mathbf{w}_{qk}, \mathbf{z}^{(k)}) = \sum_{(k=1,K)} \sum_{(k=1,K)} (\mathbf{w}_{qk}) \|\mathbf{x}^{(q)} - \mathbf{z}^{(k)}\|^2 \quad (3)$$

$$\sum_{(k=1,K)} (\mathbf{w}_{qk}) = 1 \text{ for each } q$$

$$\mathbf{w}_{qk} = (1/(\mathbf{D}_{qk})^2)^{1/(p-1)} / \sum_{(k=1,K)} (1/(\mathbf{D}_{qk})^2)^{1/(p-1)}, p > 1 \quad (4)$$

The FCM allows each feature vector to belong to every cluster with a fuzzy truth value (between 0 and 1), which is computed using Equation (4). The algorithm assigns a feature vector to a cluster according to the maximum weight of the feature vector over all clusters.

3.7 The FCM Algorithm

Based on the original FCM algorithm, we added Steps 7, 8, 9 and modified Step 2. The pseudocode of our FCM algorithm follows.

```
// K is initial number of clusters, Imax is the iteration of fuzzy
```

```
// c-means, p is for the weight
```

```
Input initial number of clusters K, Imax, p
```

```
-----step 1: -----
```

```
//initialize weights of prototype
```

```
for k = 0 to K-1
```

```
    for q = 0 to Q-1
```

```
        w[q,k] = random();
```

```
-----step 2: -----
```

```
//standardize the initial weight over K
```

```
for q = 0 to Q-1
```

```
    sum = 0.0;
```

```
    for k = 0 to K-1
```

```
        sum = sum + w[q,k];
```

```
    for k = 0 to K-1
```

```
        w[q,k] = w[q,k] /sum;
```

```
*****
```

```
// starting fuzzy c-means loop
```

```
I = 0
```

-----step 3: -----

// standardize cluster weights over Q

for k = 0 to K-1

 min = 99999.0; max = 0.0;

 for q = 0 to Q-1

 if (w[q,k] > max)

 max = w[q,k];

 if (w[q,k] < min)

 min = w[q,k];

 sum = 0.0

 for q = 0 to Q-1

 sum = sum + (w[q,k] - min) / (max - min);

 for q = 0 to Q-1

 w[q,k] = w[q,k]/sum;

-----step 4: -----

// compute new prototype center

for k = 0 to K-1

 for n = 0 to N-1

```

sum = 0.0;

for q = 0 to Q-1

    sum = sum + w[q,k] x[n,q];

z[n,k] = sum;

```

-----step 5: -----

```

// compute new weight

for q = 0 to Q-1

    sum = 0.0

    for k = 0 to K-1

        D[q,k] = 0.0;

        for n = 0 to N-1

             $D[q,k] = D[q,k] + (x[n,q] - z[n,k])^2$ 

             $sum = sum + (1/(1 + D[q,k]))^{1/(p-1)}$ ;

        for k = 0 to K-1

             $W[q,k] = (1/(1 + D[q,k]))^{1/(p-1)} / sum$ ;

```

-----step 6: -----

```

I = I + 1

```

```

If I < Imax

```

```

    Goto step 3;

```

```
// end of fuzzy c-means loop
```

```
*****
```

```
-----step 7: -----
```

```
// assign feature vector according the max weight
```

```
for q = 0 to Q-1
```

```
    maxWeight = 0.0;
```

```
    for k = 0 to K-1
```

```
        if maxWeight < weight[q,k];
```

```
            maxWeight = weight[q,k];
```

```
            kmax = k;
```

```
    cluster[q] = k;
```

```
-----step 8: -----
```

```
// eliminate clusters with no feature vectors
```

```
eliminate(0); /* call the process of eliminating clusters contains
```

less than or equal to the

number passed to it.

Here we only pass 0 for

```
this algorithm. */
```

```
-----step 9: -----
```

```

// compute arithmetic center of clusters

// calculate sigma and Xie_Beni value

.

for k = 1 to K do

    fuzzyweights();    /* Calculate fuzzy weight (Eqn. 4)

 $\sigma_2^k$  = variance();    /* Get variance (mean-square error) of

                                each cluster (Eqn. 9) */

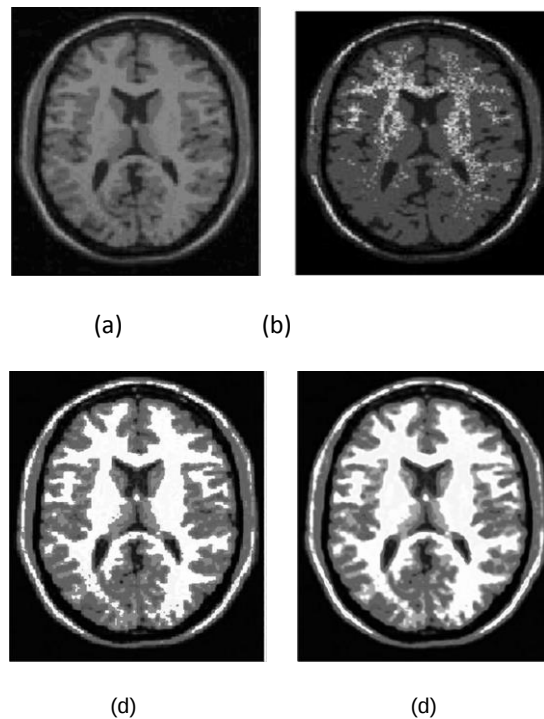
 $\kappa$  = Xie-Beni();    /* Compute modified XB (Eqn. 8) */

```

3.8 Results

In this section, we describe the application of the FCM segmentation on synthetic images corrupted with multiplicative gain and real T1 brain MR images. For compared with the FCM algorithm, we created the simulating image used by Ahmed. Simulating image is a T1-weighted phantom with in-plane high resolution, Gaussian noise with 6.0, and three-dimensional linear shading 7% in each direction. There are many advantages for using digital phantoms rather than real image including in prior knowledge of the true tissue types and control over image parameters such as mean intensity values, noise and intensity inhomogeneities. We also employed the fast algorithm for improving calculational effect , because its consumed time is 1/4 of the traditional algorithm.

For compare our new method with FCM with low SNR images, according to the reference, the parameters (the neighbors effect) for FCM are 0.85, 2, 9 (a 3 X 3 window centered around each pixel) and 0.01. Fig. 1 display the simulating image (a) and the segmentation results. It is difficult to correct using standard FCM approaches in Fig. 1(b). while the FCM algorithms have succeeded in correcting and classifying WM from the image as shown in Fig. 1(c) and (d) ($\alpha = 0.09, \sigma = 1.25$). The both estimated the bias fields and received the similar results, but FCM outperformed beyond the FCM. We employed the true ratio (TR) to evaluate the differences.



3.9 ADAPTIVE MEAN SHIFT THRESHOLDING FOR ALZHEIMER SEGMENTATION

The most popular technique, k-means clustering, however, has two inherent limitations: the clusters are constrained to be spherically symmetric and their number has to be known a priori. In nonparametric clustering methods, like the one based on mean shift, these limitations are eliminated but the amount of computation becomes prohibitively large as the dimension of the space increases. We exploit a recently proposed approximation technique. The goal of feature space analysis is to reduce the data to a few significant features through a procedure known under many different names, clustering, unsupervised learning, or vector quantization. The inputs are the brain preprocessed image. Each pixel consisted of thirty one bands in the visual spectrum. In the experiments only the photometric data were used. The x-y coordinates of the pixels were discarded. As in the previous experiments the number of clusters recovered by the mean shift clustering was used as the value of k for the k-means clustering.

An automated scheme for imaging segmentation is proposed. An adaptive mean-shift methodology is utilized in order to classify brain voxels into one of three main tissue types: gray matter, white matter, and Cerebro-spinal fluid. The image space is represented by a high-dimensional feature space that includes multimodal intensity features as well as spatial features. An adaptive mean-shift algorithm clusters the joint spatial-intensity feature space, thus extracting a representative set of high-density points within the feature space, otherwise known as modes. Tissue segmentation is obtained by a follow-up phase of intensity-based mode clustering into the three tissue categories. By its nonparametric nature, adaptive mean-shift can deal successfully with non convex clusters and produce convergence modes that are better candidates for intensity based classification than the initial voxels. The proposed method is validated on 3-D single and multimodal datasets, for oth simulated and real data. It is shown to perform well in comparison to other state-of-the-art methods without the use of a preregistered statistical brain atlas.

Medical image segmentation refers to the segmentation of known anatomic structures from medical images.

Structures of interest include organs or parts thereof, such as cardiac ventricles or kidneys, abnormalities such as Alzheimer and cysts, as well as other structures such as bones, vessels, brain structures etc. The overall objective of such methods is referred to as computer-aided diagnosis; in other words, they are used for assisting doctors in evaluating medical imagery or in recognizing abnormal findings in a medical image.

In contrast to generic segmentation methods, methods used for medical image segmentation are often application-specific; as such, they can make use of prior knowledge for the particular objects of interest and other expected or possible structures in the image. This has led to the development of a wide range of segmentation methods addressing specific problems in medical applications.

Some methods proposed in the literature are extensions of methods originally proposed for generic image segmentation. In, a modification of the watershed transform is proposed for knee cartilage and gray matter/white matter segmentation in magnetic resonance images. This introduces prior information in the watershed method via the use of a previous probability calculation for the classes present in the image and via the combination of the watershed transform with atlas registration for the automatic generation of markers.

Other methods are more application specific; for example in, segmentation tools are developed for use in the study of the function of the brain, i.e. for the classification of brain areas as activating, deactivating, or not activating, using functional magnetic resonance imaging (F) data. The method of performs segmentation based on intensity histogram information, augmented with adaptive spatial regularization using Markov random fields. The latter contributes to improved segmentation as compared to non-spatial mixture models, while not requiring the heuristic fine-tuning that is necessary for non-adaptive spatial regularization previously proposed.

Another important application of segmentation tools is in the study of the function of the heart. In, a contour detection algorithm based on a radial edge-detection filter is developed for cardiac echographic images. Objective of this algorithm is to define a region of interest in which measurements (e.g. image intensity) can lead, after appropriate interpretation, to the estimation of important cardiovascular parameters without the need for invasive techniques.

CHAPTER 4

RESULTS AND DISCUSSIONS

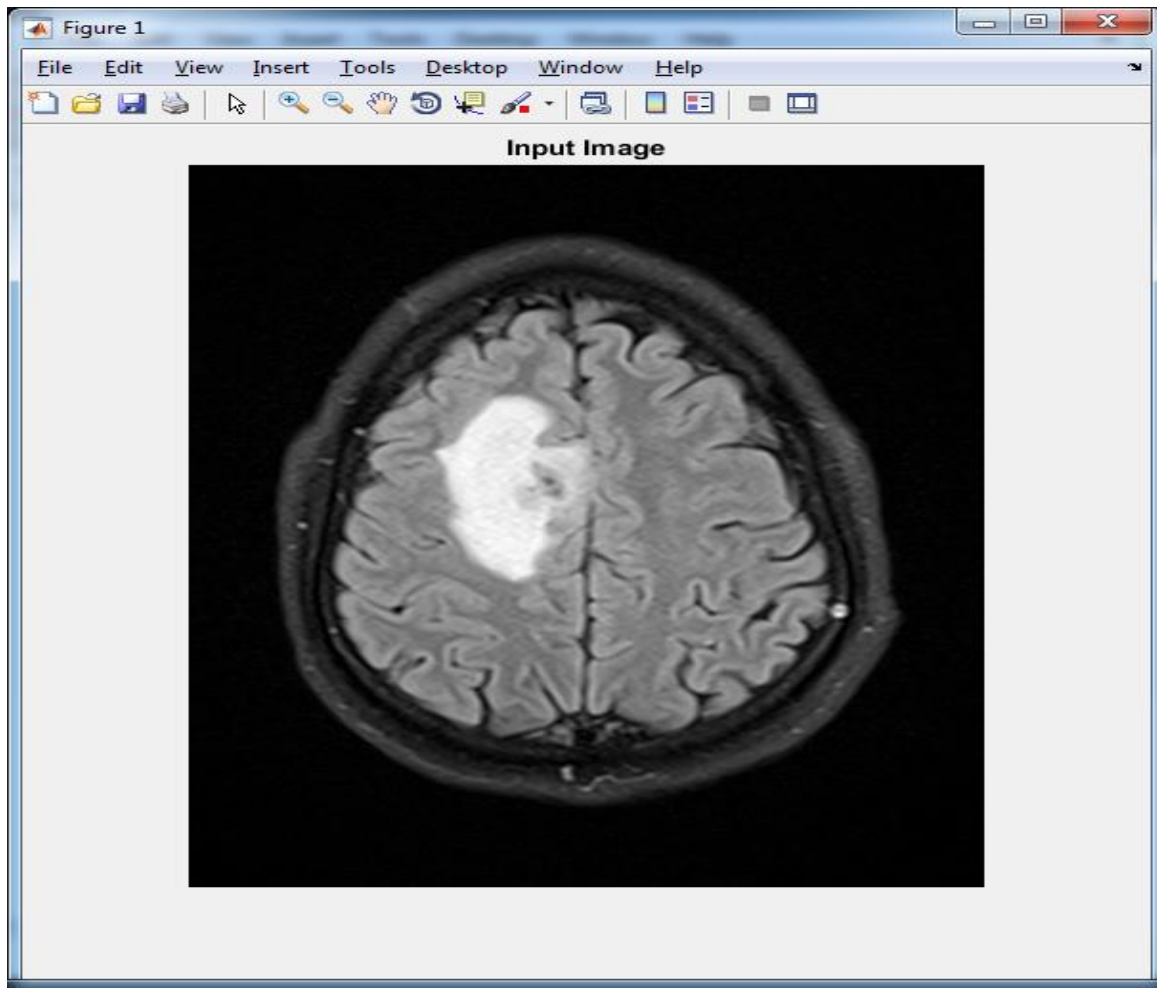


Fig. 4.1: Input Image

Figure 4.1 shows Magnetic resonance imaging (MRI) that is a noninvasive clinical tool that doctors use to analyze and treat ailments.

X-ray utilizes an amazing attractive field, radio recurrence beats and a PC to deliver point by point pictures of organs, delicate tissues, bone and practically any remaining inward body structures. X-ray doesn't utilize ionizing radiation (x-beams). Point by point MR pictures permit doctors to assess different pieces of the body and decide the presence of specific sicknesses. The pictures would then be able to be analyzed on a PC screen, communicated electronically, printed or duplicated to a CD.

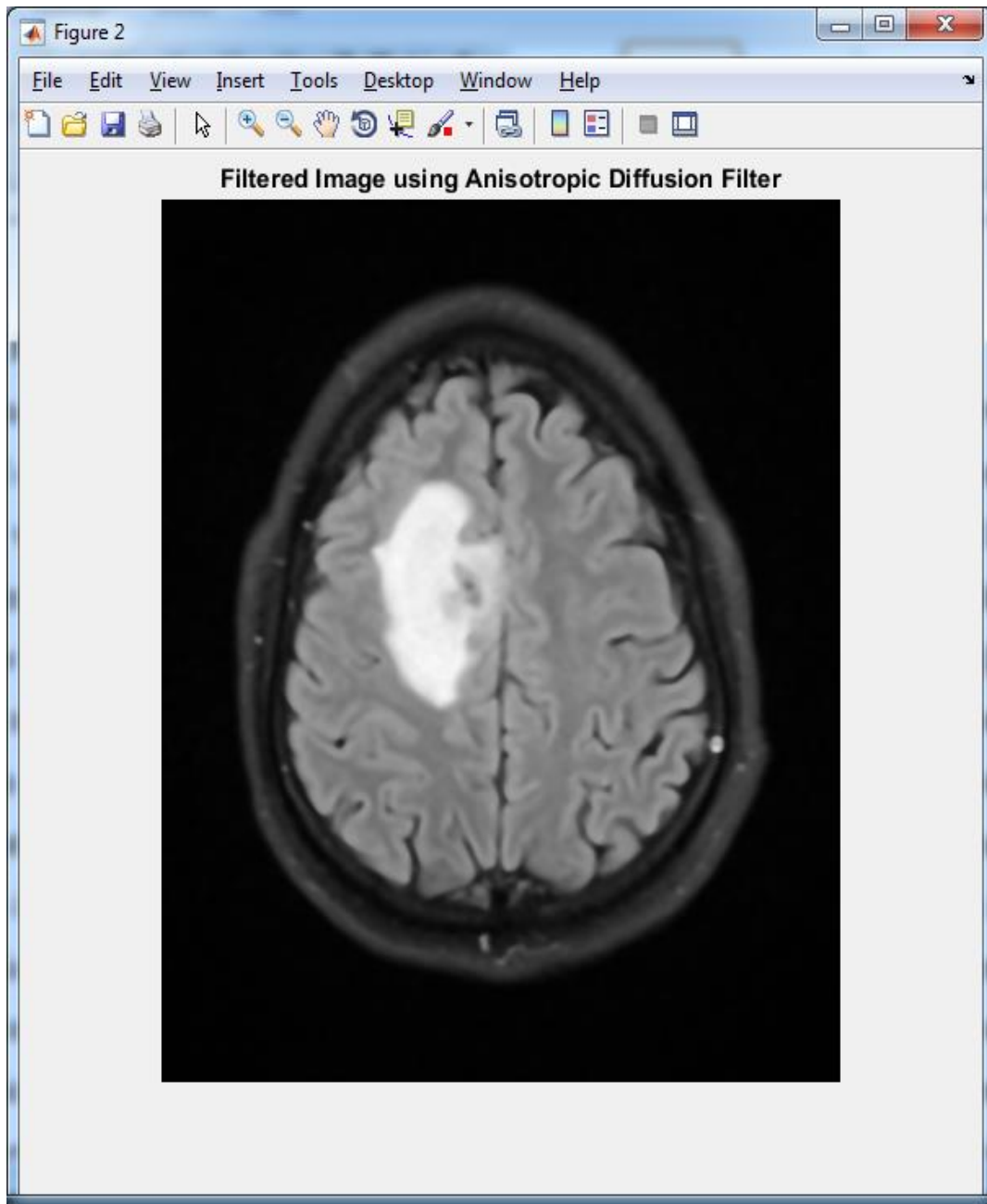


Fig: 4.2. Filter Image using Anisotropic Diffusion Filter

Figure 4.2 shows picture separating utilizing anisotropic dispersion channel. Nonlinear anisotropic dispersion sifting is a technique dependent on nonlinear advancement halfway differential conditions which tries to improve pictures subjectively by eliminating commotion while safeguarding subtleties and in any event, upgrading edges. Nonetheless, notable executions are delicate to boundaries which are essentially tuned to hone a restricted scope of edge inclines; in any case, edges are either obscured or staircased. In this work, nonlinear anisotropic dissemination channels have been created which hone edges over a wide scope of incline scales and

which decrease clamor moderately with scattering absolutely along highlight limits. In particular, the scope of honed edge slants is enlarged as in reverse dispersion typical to level sets is adjusted with forward dissemination digression to level sets. Additionally, commotion is decreased by specifically changing the equilibrium toward reducing typical in reverse dispersion and especially toward complete variety sifting. The hypothetical inspiration for the proposed channels is given together computational outcomes contrasting and other nonlinear anisotropic dispersion channels on both manufactured pictures and attractive reverberation images

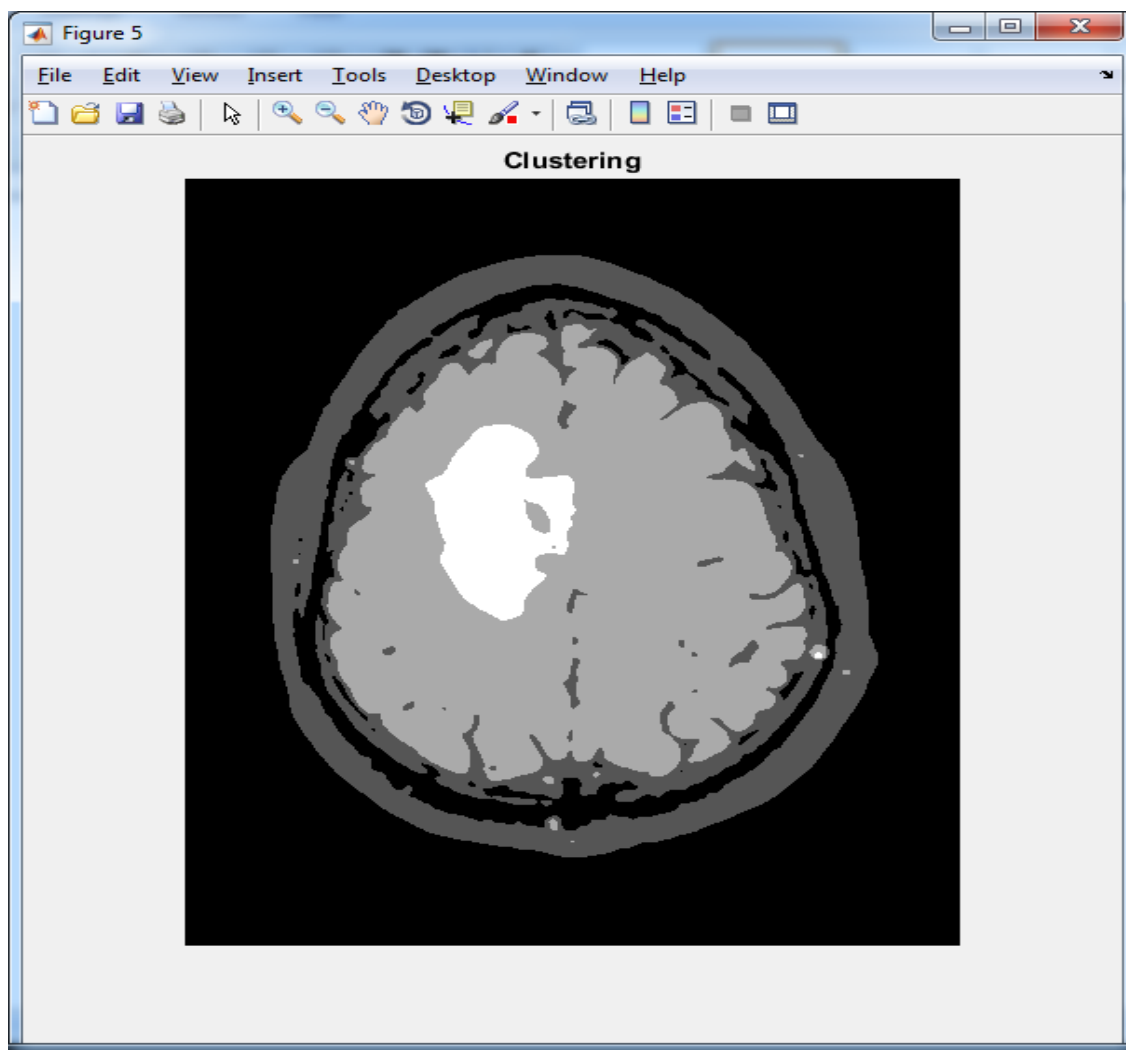


Fig: 4.3 Clustering

The figure 4.3 shows picture grouping. We present a fundamental plan and exploratory aftereffects of tumor objects following strategy for attractive reverberation imaging (MRI) mind pictures that uses shading changed over division calculation with K-implyes grouping method. The technique is fit for tackling unfit precisely molded injury objects issue in MRI picture by adding the shading based division activity. The

critical thought of shading changed over division calculation with bunching is to tackle the given MRI picture by changing over the info dark level picture into a shading space picture and working the picture marked by group list. In this paper we examine the chance of utilizing this methodology for picture based-MRI application. The use of the proposed strategy for following tumor is shown to assist pathologists with recognizing sore size and area.

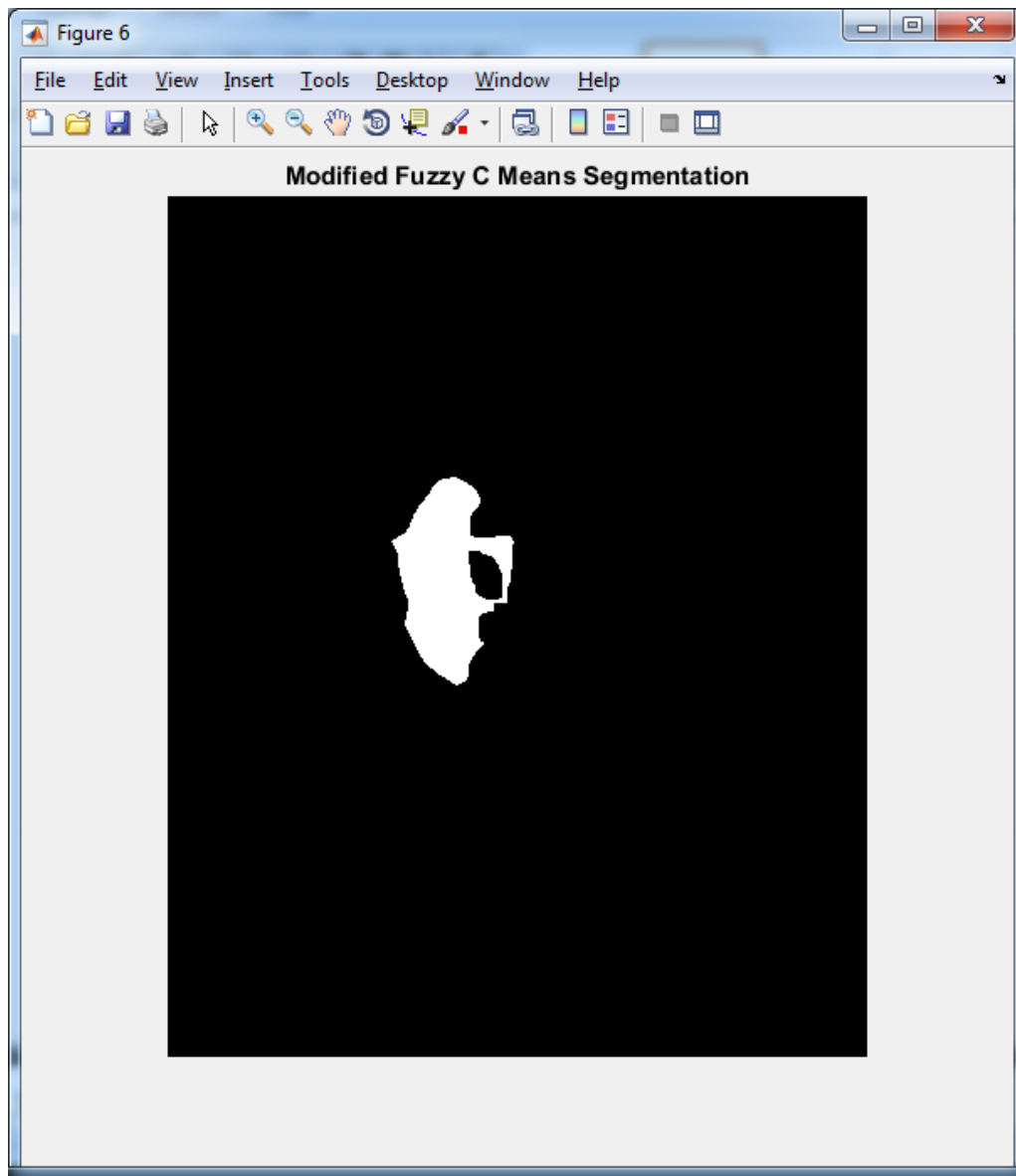


Fig: 4.4 Modified Fuzzy C Means Segmentation

The Figure 4.4 shows picture division utilizing bunching procedure. Mind tumor division in attractive reverberation imaging (MRI) is viewed as an intricate system due to the fluctuation of tumor shapes and the intricacy of deciding the tumor area, size, and surface. Alzheimer division is a tedious undertaking exceptionally inclined to

human blunder. Subsequently, this investigation proposes a mechanized technique that can recognize tumor and portion the tumor across all picture cuts in volumetric MRI mind checks. Initial, a bunch of calculations in the pre-handling stage is utilized to clean and normalize the gathered information. A changed dark level co-event grid are utilized for highlight extraction and highlight choice, individually. A multi-facet perceptron neural organization is received as a classifier, and a bouncing based calculation is utilized to recognize the area of obsessive tissues in the MRI cuts

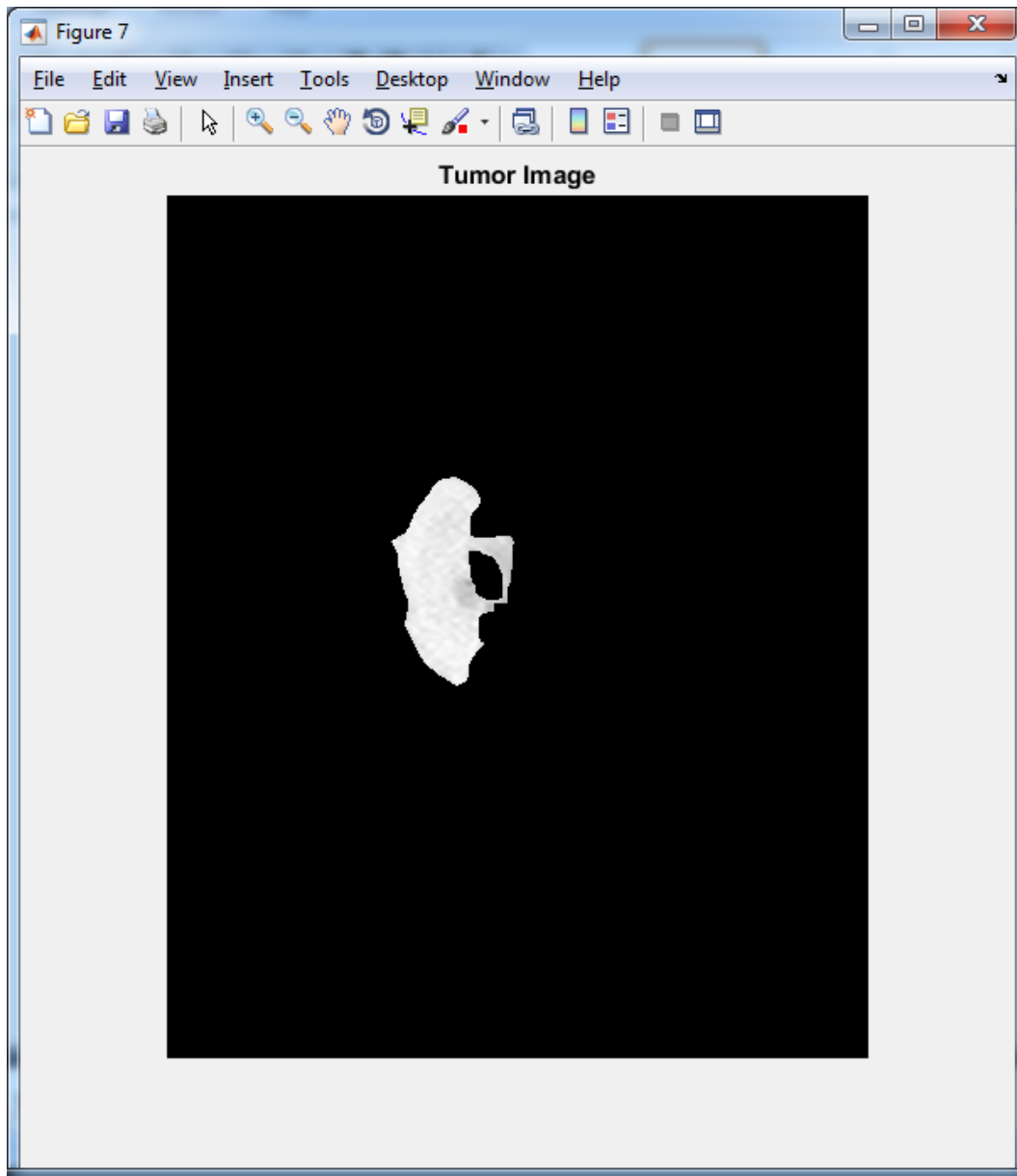


Fig. 5.5: Segmented image on super imposition with input picture

The figure 5.5 shows the sectioned picture is overly forced with input picture and portioned the district of interest.

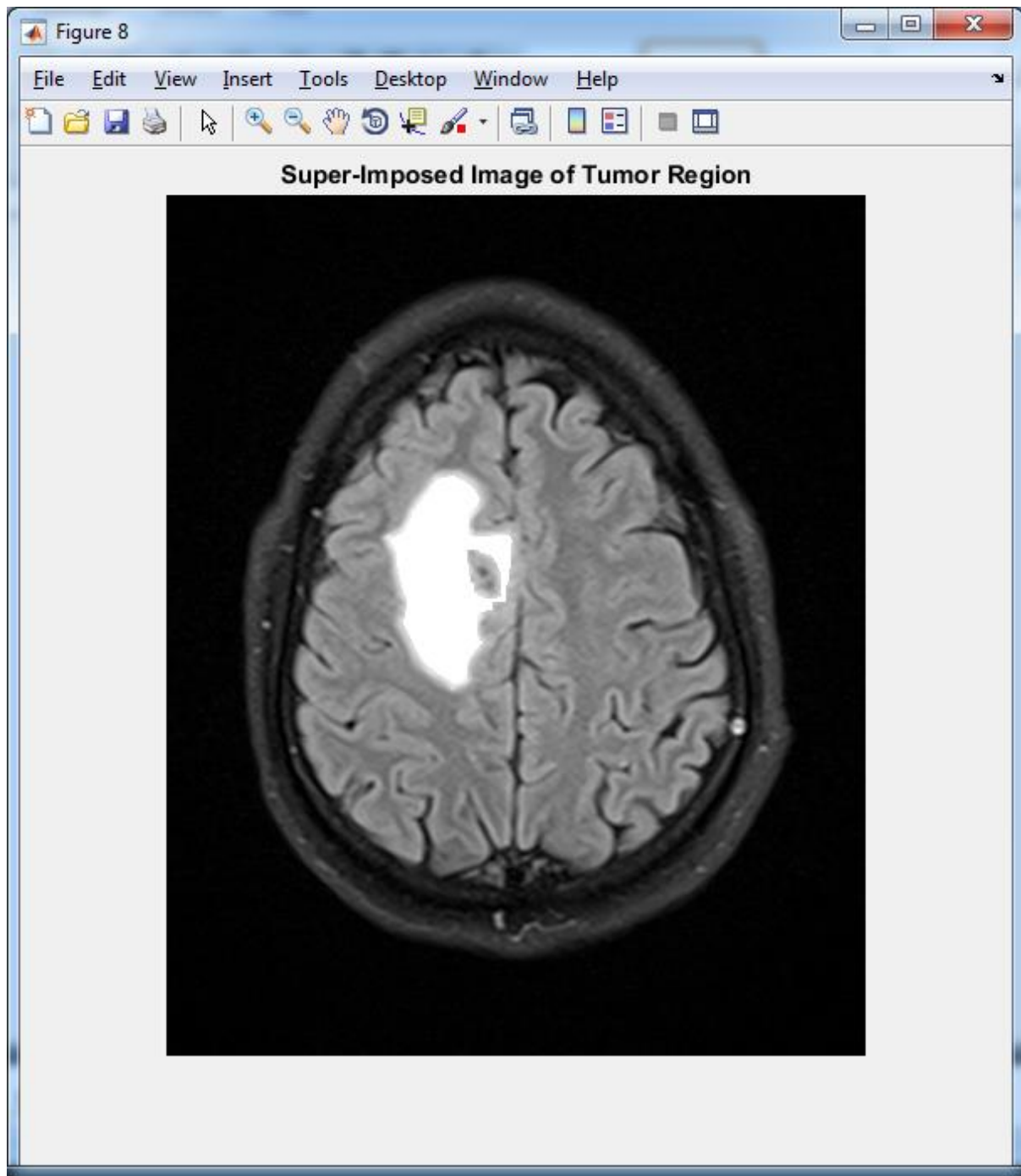


Fig. 5.6: MFCM division

The figure 5.6 shows MFCM sectioned picture with super inconvenience. Grouping approach is broadly utilized in biomedical applications especially for mind Alzheimer discovery in unusual attractive reverberation (MRI) pictures. Fluffy grouping utilizing

fluffy C-implies (FCM) calculation end up being better ludicrous bunching approaches regarding division productivity. Yet, the significant disadvantage of the FCM calculation is the colossal computational time needed for assembly. The adequacy of the FCM calculation regarding computational rate is improved by adjusting the group place and enrollment esteem refreshing model. In this paper, the utilization of adjusted FCM calculation for MR mind Alzheimer location is investigated. A thorough element vector space is utilized for the division method. Near examination as far as division proficiency and combination rate is performed between the traditional FCM and the adjusted FCM.

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CHAPTER 5

5.1 CONCLUSION

The overwhelming disadvantage of the standard FCM for picture division is that the objective element does not presently consider the spatial realities within the image, anyway adapt to photographs as like separate focuses. Accordingly, as verified in bunches of literary works the standard FCM set of rules is sensitive to commotion and a noisy pixel is generally wrongly arranged because of its abnormal element. In this paper, we proposed a pristine change FCM that contains the spatial realities into the club highlight to improve the division impacts. In the spic and span spatial component we utilized commitment components. The first got reliable with distances among basic pixels with neighbor pixels. The second thing got determined reliable with expense qualification of basic pixel with neighbor pixels. Utilizing of those commitment components incited that spatial element is manufactured from reliable with distance and expense pixels. The new method got inspected on MRI photographs and assessed through method of methods for the utilization of different bunch legitimacy capacities. Fundamental impacts affirmed that the effect of clamor in division turned out to be radically significantly less with the spic and span set of rules than with the conventional FCM.

5.2 FUTURE WORK

Planning programmed structures for mind Alzheimer extraction from a Medical Resonance Image is one of the greatest investigated areas of the period. Computerized constructions will help the clinical specialists in robotized and early degree Alzheimer discovery as an approach to allow clinical specialists to invest more noteworthy energy at the cure of the patient. This notice utilizes marker oversaw watershed division to area strangely developed mass as a top priority, called mind tumor, from an enter MR Image. 2D MRI give a restricted perspective on the brain, on this case, having an image, will give an entire and complete view of any types of irregularities living within the psyche. The system offered on this paper now not, at this point

handiest offers a concentrated perspective on the brain, anyway moreover fragments the Alzheimer with exceptional precision as portrayed through method of methods for the impacts.

5.3 REFERENCES

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