ejpmr, 2016,3(5), 176-189

SJIF Impact Factor 3.628

EUROPEAN JOURNAL OF PHARMACEUTICAL AND MEDICAL RESEARCH

www.ejpmr.com

Review Article

ISSN 2394-3211

EJPMR

BRAIN TUMOR DETECTION AND ANALYSIS FROM MRI-A REVIEW

[1]Madhurima Banerjee, [2]Ranjita Chowdhury and *[3]Prof. Samir Kumar Bandyopadhyay

[1]Dept. of Computer Science and Application, Heritage Academy, Kolkata, India.
[2]Dept.of Computer Science and Engineering, St. Thomas College of Engineering and Technology, Kolkata, India.
[3]Dept. of Computer Sc. & Engineering, University of Calcutta, Kolkata, India.

***Corresponding Author: Prof. Dr. Samir Kumar Bandyopadhyay**
Dept. of Computer Sc. & Engineering, University of Calcutta, Kolkata, India.

Article Received on 27/02/2016 **Article Revised on 19/03/2016** **Article Accepted on 10/04/2016**

ABSTRACT
Medical imaging is categorized as a part of radiological sciences. This paper reviews Brain Tumor Detection and Analysis from MRI.

KEYWORDS: MRI, PET, SPECT and fMRI.

INTRODUCTION

Recent advances in medical imaging with significant contributions from electrical and computer engineering, medical physics, chemistry and computer science have witnessed a revolutionary growth in diagnostic radiology. Fast improvements in engineering and computing technologies have made it possible to acquire high-resolution multidimensional images of complex organs to analyze structural and functional information of human physiology for computer-assisted diagnosis, treatment evaluation and intervention. Through large databases of vast amount of information such as standardized atlases of images, demographics, genomics, etc. new knowledge about physiological processes and associated pathologies is continuously being derived to improve our understanding of critical diseases for better diagnosis and management. This seminar provides an introduction to this ongoing knowledge quest.

In a general sense, medical imaging refers to the process involving specialized instrumentation and techniques to create images or relevant information about the internal biological structures and functions of the body. Medical imaging is sometimes categorized, in a wider sense, as a part of radiological sciences. This is particularly relevant because of its most common applications in diagnostic radiology.

In clinical environment, medical images of a specific organ or part of the body are obtained for clinical examination for the diagnosis of a disease or pathology. However, medical imaging tests are also performed to obtain images and information to study anatomical and functional structures for research purposes with normal as well as pathological subjects. Such studies are very important to understand the characteristic behavior of physiological processes in human body to understand and detect the onset of a pathology. Such an understanding is extremely important for early diagnosis as well as developing a knowledge base to study the progression of a disease associated with the physiological processes that deviate from their normal counterparts. The significance of medical imaging paradigm is its direct impact on the healthcare through diagnosis, treatment evaluation, intervention and prognosis of a specific disease.

From a scientific point of view, medical imaging is highly multidisciplinary and interdisciplinary with a wide coverage of physical, biological, engineering and medical sciences. The overall technology requires direct involvement of expertise in physics, chemistry, biology, mathematics, engineering, computer science and medicine so that useful procedures and protocols for medical imaging tests with appropriate instrumentation can be developed. The development of a specific imaging modality system starts with the physiological understanding of the biological medium and its relationship to the targeted information to be obtained through imaging.

Once such a relationship is determined, a method for obtaining the targeted information using a specific energy transformation process, often known as physics of imaging, is investigated. Once a method for imaging is established, proper instrumentation with energy source(s), detectors, and data acquisition systems are designed and integrated to physically build an imaging system for imaging patients to obtain target information in the context of a pathological investigation. For example, to obtain anatomical information about internal organs of the body, X-ray energy may be used. The X-ray energy, while transmitted through the body, goes through attenuation based on the density of the internal structures. Thus, the attenuation of the X-ray energy carries the target information about the density of internal structures which is then displayed as a two-dimensional (in case of radiography or mammography) or multidimensional (3D in case computed tomography (CT); 4D in case of cine-CT) image. This information (image) can be directly interpreted by a radiologist or further processed by a computer for image processing and analysis for better interpretation.[1-5]

With the evolutionary progress in engineering and computing technologies in the last century, medical imaging technologies have witnessed a tremendous growth that has made a major impact in diagnostic radiology. These advances have revolutionized healthcare through fast imaging techniques; data acquisition, storage and analysis systems; high resolution picture archiving and communication systems; information mining with modeling and simulation capabilities to enhance our knowledge base about the diagnosis, treatment and management of critical diseases such as cancer, cardiac failure, brain tumors and cognitive disorders.

There are many medical imaging modalities and techniques that have been developed in the past years. Anatomical structures can be effectively imaged today with X-ray computed tomography (CT), magnetic resonance imaging (MRI), ultrasound and optical imaging methods. Furthermore, information about physiological structures with respect to metabolism and/or functions, can be obtained through nuclear medicine [single photon emission computed tomography (SPECT) and positron emission tomography (PET)], ultrasound, optical fluorescence, and several derivative protocols of MRI such as fMRI, diffusion-tensor MRI, etc.[7-9]

The selection of an appropriate medical imaging modality is important for obtaining the target information for a successful pathological investigation. For example, if information has to be obtained about the cardiac volumes and functions associated with a beating heart, one has to determine the requirements and limitations about the spatial and temporal resolution for the target set of images. It is also important to keep in mind the type of pathology being investigated for the imaging test. Depending on the investigation, such as metabolism of cardiac walls, or opening and closing measurements of mitral valve, a specific medical imaging modality (e.g. PET) or a combination of different modalities (e.g. stress-PET and ultrasound) can be selected.[10-15]

MEDICAL IMAGING MODALITIES

Medical imaging is a process of collecting information about a specific physiological structure (an organ or tissue) using a predefined characteristic property that is displayed in the form of an image. For example, in X-ray radiography, mammography and computed tomography (CT), tissue density is the characteristic property that is displayed in images to show anatomical structures. The information about tissue density of anatomical structures is obtained by measuring attenuation to X-ray energy when it is transmitted through the body. On the other hand, a nuclear medicine positron emission tomography (PET) image may show glucose metabolism information in the tissue or organ. A PET image is obtained by measuring gamma-ray emission from the body when a radioactive pharmaceutical material, such as flurodeoxyglucose (FDG) is injected in the body. FDG metabolizes with the tissue through blood circulation eventually making it a source of emission of gamma-ray photons. Thus, medical images may provide anatomical, metabolic or functional information related to an organ or tissue. These images through proper instrumentation and data collection methods can be primarily reconstructed in two- or three-dimensions and then displayed as multidimensional data sets.[16-17]

The basic process of image formation requires an energy source to obtain information about the object that is displayed in the form of an image. Some form of radiation such as optical light, X-ray, gamma-ray, RF or acoustic waves, interacts with the object tissue or organ to provide information about its characteristic property. The energy source can be external (X-ray radiography, mammography, CT, ultrasound), internal [nuclear medicine: single photon emission computed tomography (SPECT); positron emission tomography (PET)], or a combination of both internal and external such as in magnetic resonance imaging where proton nuclei that are available in the tissue in the body provides electromagnetic RF energy based signals in the presence of an external magnetic field and a resonating RF energy source.

As described above, image formation requires an energy source, a mechanism of interaction of energy with the object, an instrumentation to collect the data with the measurement of energy after the interaction and a method of reconstructing images of information about the characteristic property of the object from the collected data.

MAGNETIC RESONANCE IMAGING

The principle of nuclear magnetic resonance for medical imaging was first demonstrated by Raymond Damadian in 1971 and Paul Lauterbur in 1973. Nuclear magnetic resonance (NMR) is a phenomenon of magnetic systems that possesses both a magnetic moment and an angular moment. In magnetic resonance imaging (MRI), the electromagnetic induction based signals at magnetic resonance frequency in the radio frequency (RF) range are collected through nuclear magnetic resonance from the excited nuclei with magnetic moment and angular momentum present in the body.

All materials consist of nuclei which are protons, neutrons or a combination of both. Nuclei that contain an odd number of protons, neurons or both in combination possess a nuclear spin and a magnetic moment. Most materials are composed of several nuclei which have the magnetic moments such as 1H, 2H, 13C, 31Na, etc. When such material is placed number a magnetic field, randomly oriented nuclei experience an external magnetic torque which aligns the nuclei either in a parallel or an antiparallel direction in reference to the external magnetic field. The number of nuclei aligned in parallel is greater by a fraction than the number of nuclei aligned in an antiparallel direction and is dependent on the strength of the applied magnetic field. Thus, a net vector results in the parallel direction. The nuclei under the magnetic field rotate or precess like spinning tops precessing around the direction of the gravitational field. The rotating or precessional frequency of the spins is called the Larmor precession frequency and is proportional to the magnetic field strength. The energy state of the nuclei in the antiparallel direction is higher than the energy state of the nuclei in the parallel direction. When an external electromagnetic radiation at the Larmor frequency is applied through the RF coils (because the natural magnetic frequency of these nuclei fall within the radiofrequency range), some of the nuclei directed in the parallel direction get excited and go to the higher energy state, becoming in the direction antiparallel to the external magnetic field to the antiparallel direction. The lower energy state has the larger population of spins than the higher energy states. Thus, through the application of the RF signal, the spin population is also affected.

When the RF excitation signal is removed, the excited portions tend to return to their lower energy states through relaxation resulting in the recovery of the net vector and the spin population. The relaxation process causes the emission of a RF frequency signal at the same Larmor frequency which is received by the RF coils to generate an electric potential signal called the free-induction decay (FID). This signal becomes the basis of MR imaging.

DICOM FILES

DICOM (Digital Imaging and Communications in Medicine) is a standard for handling, storing, printing, and transmitting information in medical imaging. It includes a file format definition and a network communications protocol. The communication protocol is an application protocol that uses TCP/IP to communicate between systems. DICOM files can be exchanged between two entities that are capable of receiving image and patient data in DICOM format. The National Electrical Manufacturers Association (NEMA) holds the copyright to this standard. It was developed by the DICOM Standards Committee, whose members are also partly members of NEMA.

DICOM enables the integration of scanners, servers, workstations, printers, and network hardware from multiple manufacturers into a picture archiving and communication system (PACS). The different devices come with DICOM conformance statements which clearly state the DICOM classes they support. DICOM has been widely adopted by hospitals and is making inroads in smaller applications like dentists' and doctors' offices.

DICOM is known as NEMA standard PS3, and as ISO standard 12052:2006 "Health informatics -- Digital imaging and communication in medicine (DICOM) including workflow and data management".

DICOM DATA FORMAT

DICOM differs from some, but not all, data formats in that it groups information into data sets. That means that a file of a chest X-Ray image, for example, actually contains the patient ID within the file, so that the image can never be separated from this information by mistake. This is similar to the way that image formats such as JPEG can also have embedded tags to identify and otherwise describe the image.

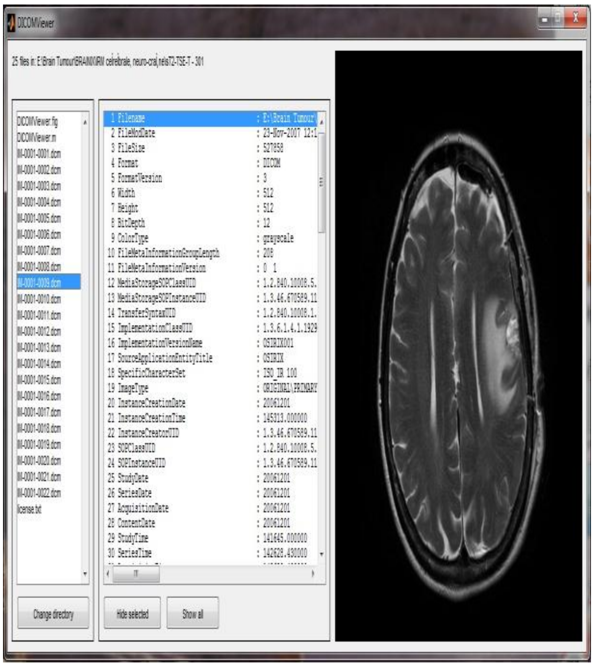
A DICOM data object consists of a number of attributes, including items such as name, ID, etc., and also one special attribute containing the image pixel data (i.e. logically, the main object has no "header" as such: merely a list of attributes, including the pixel data). A single DICOM object can only contain one attribute containing pixel data. For many modalities, this corresponds to a single image. But note that the attribute may contain multiple "frames", allowing storage of cine loops or other multi-frame data. Another example is NM data, where an NM image by definition is a multi-dimensional multi-frame image. In these cases three- or four-dimensional data can be encapsulated in a single DICOM object. Pixel data can be compressed using a variety of standards, including JPEG, JPEG Lossless, JPEG 2000, and Run-length encoding (RLE). LZW (zip) compression can be used for the whole data set (not just the pixel data) but this is rarely implemented.

DICOM uses three different Data Element encoding schemes. With Explicit Value Representation (VR) Data Elements, for VRs that are not OB, OW, OF, SQ, UT, or UN, the format for each Data Element is: GROUP (2 bytes) ELEMENT (2 bytes) VR (2 bytes) Length In Byte (2 bytes) Data (variable length). For the other Explicit Data Elements or Implicit Data Elements, vide section 7.1 of Part 5 of the DICOM Standard.

The same basic format is used for all applications, including network and file usage, but when written to a file, usually a true "header" (containing copies of a few key attributes and details of the application which wrote it) is added.

DICOM VIEWER

A GUI based viewer for DICOM image files is developed as part of this project, using MATLAB. The interface has three parts, first, the interface has options to select the folder containing the DICOM images and select the individual image from the list of available DICOM images. On selection of a particular image, the viewer displays the image in a sub window with zooming options and it also displays all the meta data available with the image like image size, dimension, time of capture etc in a third sub window. The interface also provides option to change directory to reach to other DICOM images. The screen shot of the interface is as follows:



SEGMENTATION OF BRAIN MRI IMAGE – A REVIEW

Automated brain tumor detection from MRI images is one of the most challenging task in today's modern Medical imaging research. Magnetic Resonance Images are used to produce images of soft tissue of human body. It is used to analyze the human organs without the need for surgery. Automatic detection requires brain image segmentation, which is the process of partitioning the image into distinct regions, is one of the most important and challenging aspect of computer aided clinical diagnostic tools. Noises present in the Brain MRI images are multiplicative noises and reductions of these noises are difficult task. The minute anatomical details should not be destroyed by the process of noise removal from clinical point of view. These makes accurate segmentation of brain images a challenge. However, accurate segmentation of the MRI images is very important and crucial for the exact diagnosis by computer aided clinical tools. A large variety of algorithms for segmentation of MRI images had been developed. In this paper, we present a review of the methods used in brain MRI image segmentation. The review covers imaging modalities, magnetic resonance imaging and methods for noise reduction and segmentation approaches. The paper concludes with a discussion on the upcoming trend of advanced researches in brain image segmentation.[18-23]

The past few years had witnessed a rapid and multi directional increase in the applications of image processing. In today's digital era, capturing, storing and analysis of medical image had been digitized. Even with state – of – the – art techniques, detailed interpretation of medical image is a challenge from the perspective of time and accuracy. The challenge stands tall especially in regions with abnormal color and shape which needs to be identified by radiologists for future studies. The key task in designing such image processing and computer vision applications is the accurate segmentation of medical images. Image segmentation is the process of partitioning different regions of the image based on different criteria.

Surgical planning, post-surgical assessment, abnormality detection and many other medical application requires medical image segmentation. In spite of wide number of automatic and semi – automatic image segmentation techniques, they fail in most cases largely because of unknown and irregular noise, in homogenity, poor contrast and weak boundaries which are inherent to medical images. MRI and other medical images contain complicated anatomical structures that require precise and most accurate segmentation for clinical diagnosis.

Brain image segmentation from MRI images is complicated and challenging but its precise and exact segmentation is necessary for tumors detection and their classification, edema, haemorage detection and necrotic tissues. For early detection of abnormalities in brain parts, MRI imaging is the most efficient imaging technique. Unlike computerized Tomography (CT), MRI image acquisition parameters can be adjusted for generating high contrast image with different gray level for various cases of neuropathology. Therefore, MRI image segmentation stands in the upcoming research limelight in medical imaging areana.

In the field of neuroscience, mapping of functional activation onto brain anatomy, the study of brain development, and the analysis of neuroanatomical variability in normal brains requires the identification of brain structures in MRI images. Apart from this, segmentation of MRI images is essential in clinical diagnosis of neurodegenerative and psychiatric disorders, treatment evaluation, and surgical planning.

Segmentation is the process of partitioning an image to several segments. The main difficulties in segmentation are:

- Noise
- The bias field (the presence of smoothly varying intensities inside tissues)
- The partial-volume effect (a voxel contributes in multiple tissue types)

EXISTING DE-NOISING METHODS

In spite of the presence of substantial number of state – of – the – art methods of de – noising but accurate removal of noise from MRI image is a challenge. Methods such as use of standard filters to more advanced filters, nonlinear filtering methods, anisotropic nonlinear diffusion filtering, a Markov random field (MRF) models, wavelet models, non-local means models (NL-means) and analytically correction schemes.

These methods are almost same in terms of computation cost, de-noising, quality of de-noising and boundary preserving. So, de-noising is still an open issue and de-noising methods needs improvement. Linear filters reduce noise by updating pixel value by weighted average of neighborhood but degrade the image quality substantially. On the other hand, non linear filters preserve edges but degrade fine structures.

A Markov random field method (MRF)

In this method spatial correlation information is used to preserve fine detail, i.e., spatial regularization of the noise estimation is performed. In MRF method, the updation of pixel value is done by iterated conditional modes and simulated annealing with maximizing a posterior estimate.

Wavelet-based methods

In frequency domain these method is used for de – noising and preserving the signal. Application of wavelet based methods on MRI images makes the wavelet and scaling coefficients biased. This problem is solved by squaring the MRI image by non central chi – square distribution method. These make the scaling coefficients independent of the signal and thus can be easily removed. In case of low SNR images, finer details are not preserved.

Analytical correction method

This method attempts to estimate noise and subsequently noise-free signal from observed image. This method uses maximum likelihood estimation (MLE) to estimate noise and subsequently generate noise free images. Neighborhood smoothing is used to estimate noise free image by considering signal in small region to be constant. Edges in the image are degraded.

Non-local (NL)

This method exploits the redundant information in images. The pixel values are substituted by taking weighted average of neighborhood similar to the neighborhood of the image. MRI images, consists of non-repeated details due to noise, complicated structures, blur in acquisition and the partial volume effect originating from the low sensor resolution that is eliminated by this method.

Image segmentation methods

Techniques such as thresholding, the region growing, statistical models, active control models and clustering have been used for image segmentation. Because of the complex intensity distribution in medical images, thresholding becomes a difficult task and often fails. In the region growing method, thresholding is combined with connectivity.

Fuzzy C – means is a popular method for medical image segmentation but it only considers image intensity thereby producing unsatisfactory results in noisy images. A bunch of algorithms are proposed to make FCM robust against noise and in homogeneity but it's still not perfect.

Accurate estimation of the probability density function (PDF) is essential in probabilistic classification. Nonparametric approach does not make any assumption in obtaining the parameters of PDF thereby making it accurate but expensive. In parametric approaches, a function is assumed to be a PDF function. It is easy to implement but sometimes lacks accuracy and does not match real data distribution.

FCM

Firstly, the algorithm selects the initial cluster centers from SOM clustering algorithm. Then, after many iterations of the algorithm, the final result converges to actual cluster center. Thereby, a good set of initial cluster is generated. The winning neural units and their corresponding weight vectors from each layer result in an abstraction tree. The region of the image at a specified level of abstraction is represented by a node of the abstraction tree. Segmentation of image is generated on demand by traversing the abstraction tree in the BFS manner starting from the root node until some criterion is satisfied. The sum of the variances of weight vector divided by size of the weight vector is less than element of weight vector if the size of the abstraction tree (weight vector) is expanded. Else the node is labeled as a closed node and none of its descendants are visited. Regions corresponding to the closed nodes constitute a segmented image and the resulting segmented image contains the regions from different abstraction levels.

L VQ

Learning vector quantization (LVQ) is a supervised competitive learning technique that obtains decision boundaries in input space based on training data. It defines class boundaries prototypes, a nearest-neighbor rule and a winner-takes-it-all paradigm. LVQ is composed of three layers: input layer, competitive layer and output layer. The input data is classified in the competitive layer and those classes or patterns are mapped to target class in the output layer. In the learning phase weights of neurons are adjusted based on training data. The winner neuron is calculated based on the Euclidean distance, then the weight of the winner neuron is adjusted. There are several algorithms to learn LVQ networks.

SOM

Self-organizing maps (SOM) is an unsupervised clustering network that maps inputs which can be high dimensional to one or two dimensional discrete lattice of neuron units. The input data is organized into several patterns according to a similarity factor like Euclidean distance and each pattern assigns to a neuron. Each neuron has a weight that depends on the pattern assigned to that neuron. Input data is classified according to their grouping in input space and neighboring neuron and moreover learns distribution and topology of input data. SOP consists of two layers: first is the input layer and the number of neurons in this layer is equal to dimension of input and second is the competitive layer and each neuron in this layer corresponds to one class or pattern. The number of neurons in this layer depends on the number of clusters and is arranged in regular geometric mesh structure. Each connection from input layer to a neuron in competitive layer is assigned with a weight vector.

The SOM functions in two steps, viz, firstly finding the winning neuron i.e. the most similar neuron to input by a similarity factor like Euclidean distance, and secondly, updating the weight of winning neuron and its neighbor pixels based on input.

Hybrid SOM

HSOM is the combines self -organization and topographic mapping technique. HSOM combines the idea of regarding the image segmentation process as one of data abstraction where the segmented image is the final domain independent abstraction of the input image. The HSOM is organized in a pyramidal mannered structure consisting of multiple layers where each layer resembles the single layer SOM. Learning process has sequential corrections of the vectors representing neurons. On every step of the learning process a random vector is chosen from the initial data set and then the best-matching neuron coefficient vector is identified. The most similar to the input vector is selected as a winner.

Watersheds

Watershed is a gradient-based segmentation technique where different gradient values are considered as different heights. A hole is made in each local minimum and immersed in water, the water will rise until local maximums. When two body of water meet, a dam is built between them. The water rises gradually until all points in the map are immersed. The image gets segmented by the dams. The dams are called watersheds and the segmented regions are called catchments basins. The over segmentation problem still exists in this method.

The region growing

The region growing starts with a seed, which is selected in the centre of the tumor region. During the region growing phase, pixels in the neighbor of seed are added to region based on homogeneity criteria thereby resulting in a connected region.

Active control model

The active control model is a framework for delineating an object outline from a noisy image and is based on a curve, $X(s) = [x(s), y(s)]$, defined in the image domain where s in range of [0,1] is an arc length. It deforms in a way that minimizes an energy function.

The term on the right hand side is the internal energy and is used to control the tension and rigidity of the deforming curve. The last term is the external energy that is used to guide the deforming curve toward the target.

Gaussian Gradient Force is used to compute external force. Advantages of this method are insensitiveness to contour initialization, boundary concavities, saving computation time, and high accuracy.

A Markov random field models

A Markov random field, Markov network or undirected graphical model is a set of random variables having a Markov property described by an undirected graph. It is a statistical model used to model spatial relations that exist in the neighbor of pixels. Image segmentation methods use MRF to take advantage of neighborhood information in the segmentation process, like, in medical images most neighborhood pixels have the same class and thus by using neighborhood information, influence of noise in segmentation is decreased.

Graph cut based

Here, the problem of image segmentation is considered as a graph partitioning problem and global criterion that measures both total dissimilarity among the different groups and the total similarity inside then is used. An efficient method based on generalized eigen value treatment is used to optimize the criterion to segment image.

Segmentation for brain with anatomical deviations

The main challenge lies in segmentation of brain with anatomical deviation like tumor with different shape, size, location and intensities. The tumor not only changes the part of brain which tumor exists but also sometimes it influences shape and intensities of other structures of the brain. Thus the existence of such anatomical deviation makes use of prior information about intensity and spatial distribution challenging. Segmentation of the tumor, its surrounding edema and other structures of the brain is very important for treatment and surgical planning.

FFT based Segmentation for brain

Noises present in the medical images are multiplicative noises and reductions of these noises are difficult task. The anatomical details should not be destroyed by the denoising process from clinical point of view. Spectral leakage has the effect of the frequency analysis of finite-length signals or finite-length segments of infinite signals. In brain the tumor itself, comprising a necrotic (dead) part and an active part, the edema or swelling in the nearby brain. As all tumor do not have a clear boundary between active and necrotic parts there is need to define a clear boundary between edema and brain tissues. It shows that some energy has leaked out of the original signal spectrum into other frequencies. A radix-4 FFT recursively partitions a DFT into four quarter-length DFTs of groups of every fourth time sample. The total computational cost reduced by these shorter FFTs outputs which are reused for computing the output.

Performance Analysis Parameters

Receiver operating characteristic (ROC) analysis is considered a statistical measure for studying the performance of an imaging or diagnostic system with respect to its ability to detect a system's ability to detect abnormalities accurately and reliably (true positive) without providing false detections. In other words, ROC analysis provides a systematic analysis of sensitivity and specificity of a diagnostic test.

True positive = The number of image which are correctly identified
False positive = The number of image which are incorrectly identified
True negative = The number of image which are correctly rejected
False negative = The number of image which are incorrectly rejected

Accuracy is a level of measurement that yields true (no systematic errors) and consistent (no random errors) results. That is, the accuracy is the proportion of true results (both true positives and true negatives) among the total number of cases observed.

Accuracy = (TP+TN) / (TP+TN+FP+FN)
Sensitivity (also called the true positive rate, or the recall in some fields) measures the proportion of positives that are correctly identified, that is, fraction of relevant instances that are retrieved.
Sensitivity = TP / (TP+FN)
Specificity (also called the true negative rate) measures the proportion of negatives that are correctly identified
Specificity = TN/(TN+FP)

Segmentation of Brain Tumor from Multiple MRI images

Here we had been working with multiple MRI Images. In the pre – processing section we have been doing two operations primarily. Firstly, the multiple images of the brain are registered with respect to one base image. So Multiple Image registration needs to be done.

Image registration, as it was mentioned above, is widely used in remote sensing, medical imaging, computer vision etc. In general, its applications can be divided into four main groups according to the manner of the image acquisition: Different viewpoints (multi view analysis). Images of the same scene are acquired from different viewpoints. The aim is to gain larger a 2D view or a 3D representation of the scanned scene. Examples of applications: Remote sensing—mosaicking of images of the surveyed area. Computer vision—shape recovery (shape from stereo). Different times (multi temporal analysis). Images of the same scene are acquired at different times, often on regular basis and possibly under different conditions. The aim is to find and evaluate changes in the scene which appeared between the consecutive image acquisitions. Examples of applications: Remote sensing—monitoring of global land usage, landscape planning. Computer vision—automatic change detection for security monitoring, motion tracking.

Medical imaging—monitoring of the healing therapy, monitoring of the tumor evolution. Different sensors (multimodal analysis). Images of the same scene are acquired by different sensors. The aim is to integrate the information obtained from different source streams to gain more complex and detailed scene representation. Examples of applications: Remote sensing—fusion of information from sensors with different characteristics like panchromatic images, offering better spatial resolution, color/multispectral images with better spectral resolution, or radar images independent of cloud cover and solar illumination. Medical imaging—combination of sensors recording the anatomical body structure like magnetic resonance image (MRI), ultrasound or CT with sensors monitoring functional and metabolic body activities like positron emission tomography (PET), single photon emission computed tomography (SPECT) or magnetic resonance spectroscopy (MRS). Results can be applied, for instance, in radiotherapy and nuclear medicine.

Scene to model registration. Images of a scene and a model of the scene are registered. The model can be a computer representation of the scene, for instance maps or digital elevation models (DEM) in GIS, another scene with similar content (another patient), 'average' specimen, etc. The aim is to localize the acquired image in the scene/model and/or to compare them. Examples of applications: Remote sensing—registration of aerial or satellite data into maps or other GIS layers. Computer vision—target template matching with real-time images, automatic quality inspection.

Medical imaging — comparison of the patient's image with digital anatomical atlases, specimen classification. Due to the diversity of images to be registered and due to various types of degradations it is impossible to design a universal method applicable to all registration tasks. Every method should take into account not only the assumed type of geometric deformation between the images but also radiometric deformations and noise corruption, required registration accuracy and application-dependent data characteristics. Nevertheless, the majority of the registration methods consists of the following four steps.

Feature detection. Salient and distinctive objects (closed-boundary regions, edges, contours, line intersections, corners, etc.) are manually or, preferably, automatically detected. For further processing, these features can be represented by their point representatives (centers of gravity, line endings, distinctive points), which are called control points (CPs) in the literature.

Feature matching. In this step, the correspondence between the features detected in the sensed image and those detected in the reference image is established. Various feature descriptors and similarity measures along with spatial relationships among the features are used for that purpose.

Transform model estimation. The type and parameters of the so-called mapping functions, aligning the sensed image with the reference image, are estimated. The parameters of the mapping functions are computed by means of the established feature correspondence.

Image resampling and transformation. The sensed image is transformed by means of the mapping functions. Image values in non-integer coordinates are computed by the appropriate interpolation technique.

Histogram based automatic image registration – based on the histogram of two images, their relative ROI is estimated
Rigid Geometric transformation based registration is used.
Rotation – up to a maximum of 90 Degree is used.
Translation
Interpolation based zoom in/out

Intensity guided – intensity of the images makes the final positioning of the image for registration.

After registering the images with respect to a base image, those images are fused to form a high definition image.

The most important issue concerning image fusion is to determine how to combine the sensor images. In recent years, several image fusion techniques have been proposed. The primitive fusion schemes perform the fusion right on the source images. One of the simplest of these image fusion methods just takes the pixel-by-pixel gray level average of the source images. This simplistic approach often has serious side effects such as reducing the contrast. With the introduction of pyramid transform in mid-80's, some more sophisticated approaches began to emerge. It was found that better results were obtained if the fusion was performed in the transform domain. The pyramid transform appears to be very useful for this purpose.

The basic idea is to perform a multiresolution decomposition on each source image, then integrate all these decompositions to form a composite representation, and finally reconstruct the fused image by performing an inverse multi-resolution transform. Several types of pyramid decomposition or multi-scale transform are used or developed for image fusion, such as, Laplacian Pyramid, Ratio-of-low-pass Pyramid, Morphological Pyramid, Gradient Pyramid and more recently, with the development of wavelet theory, the multi-scale wavelet decomposition has begun to take the place of pyramid decomposition for image fusion. Actually, the wavelet transform can be considered to be one special type of pyramid decompositions. It retains most of the advantages for image fusion but has much more complete theoretical support.

The developed system fuses/combines/mixes 2 images. It supports both Gray & Color Images. DIACOM Images are also supported. In the program, Alpha Factor can be varied to vary the proportion of mixing of each image. With Alpha Factor = 0.5, the two images are mixed equally. With Alpha Facotr < 0.5, the contribution of background image will be more. With Alpha Facotr > 0.5, the contribution of foreground image will be more.

After successful image fusion, the fused high definition image is used for segmentation of gray matter, white matter and cerebro spinal fluid using the previously proposed advanced K – means algorithm with dual localization method.

The segmentation process proposed here is a three step refining segmentation process. The three steps are:
K - means algorithm based segmentation.
Local standard deviation guided grid based coarse grain localization.
Local standard deviation guided grid based fine grain localization.

The problem of image segmentation is nothing but a classical clustering problem where the range of image gray values is clustered in some fixed number of clustered gray values. One of the simplest unsupervised learning algorithms that solve the well-known clustering problem is the K-means.[24-28] The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early groupage is done. At this point we need to re-calculate k new centroids 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. In other words centroids do not move any more.

Finally, this algorithm aims at minimizing an objective function, in this case a squared error function where the square is calculated of the distance measured between a data point and the cluster centre, that is the indicator of the distance of the n data points from their respective cluster centre.

The algorithm runs through the following steps:
Place K points into the space represented by the objects that are being clustered. These points represent initial group centroids.

Assign each object to the group that has the closest centroid.

When all objects have been assigned, recalculate the positions of the K centroids.

Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated.

Although it can be proved that the procedure will always terminate, the k-means algorithm does not necessarily find the most optimal configuration, corresponding to the global objective function minimum. The algorithm is also significantly sensitive to the initial randomly selected cluster centers.

So, to obtain an optimal segmentation cluster configuration we propose a standard local deviation guided grid based coarse grain localization after the K - means algorithm segmentation. Here, we first calculate the local standard deviation of the k - means segmented image. Here the image is mapped on large grid layout, ideally each grid is of size 8 – by – 8 i.e. 64 pixels. Local standard deviation of each pixel is calculated based on the pixel values of these 64 pixel of that grid. Then the histogram of each grid id calculated and based on the local standard deviation and histogram in each grid, the segmentation boundaries in that grid are reevaluated to generate more optimal segmentation. Choosing a large grid dimension helps us reduce the effect of noise in segmenting the grid. But, conversely, the large grid dimension also ignores the finer anatomic details such as twists and turns in the boundary of the tumor or overlapping region of gray and white matters in the brain.

So, finally to obtain the most optimal segmentation, we once more process the above segmented image using the same concept of standard local deviation guided grid based fine grain localization. Here we chose the grid size ideally to be 3 – by – 3. So, choosing a small grid helps in zeroing on the finer anatomical details of the MRI image that needs to be preserved. This helps in restoring the acute details of the tumor boundary and finer analysis of the overlap region of gray matter and white matter.

Post – processing: Extracting WM, GM and Tumor
After the successful completion of the above mentioned three step segmentation process, the histogram of the segmented image is calculated. The analysis of the image histogram shows the distinct peaks in three different image pixel gray value corresponding to gray matter, white matter and tumor. Based on this histogram, the corresponding gray matter, white matter and tumor is extracted.

Post – processing: Analysis of Tumor Dimension
A line scan method is applied to the image of the extracted tumor after the segmentation process and the maximum breadth and length of the tumor along the x – axis and y – axis is estimated.

Test results (Image Registration)

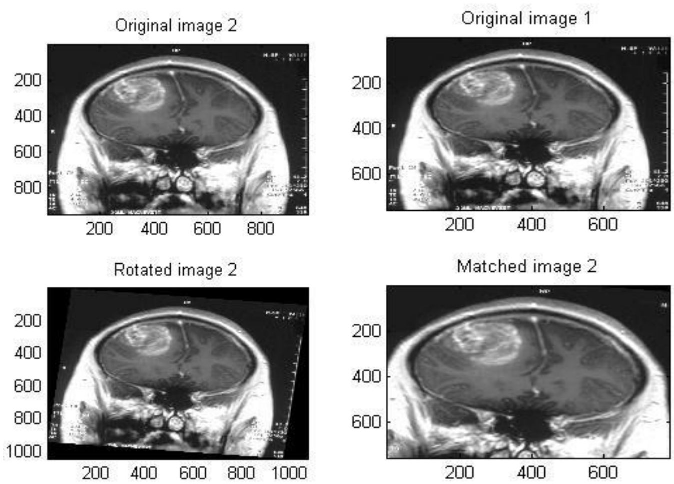
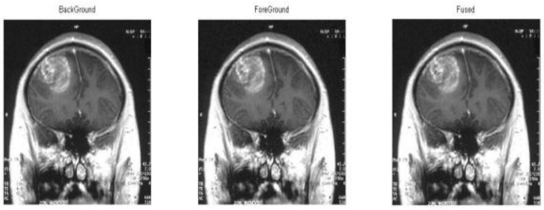
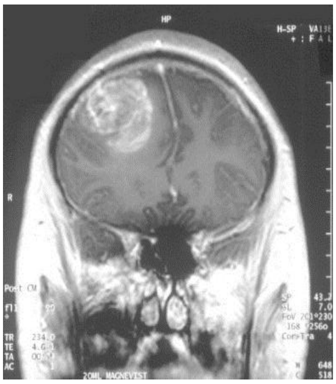
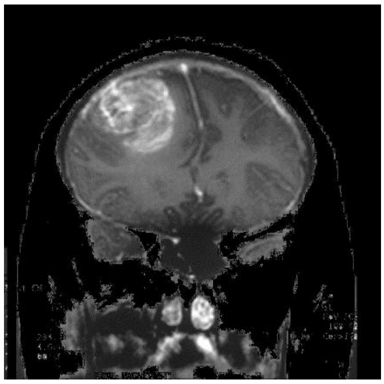


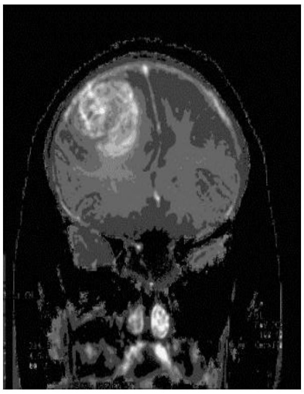
Image Fusion



Segmentation


Input Image

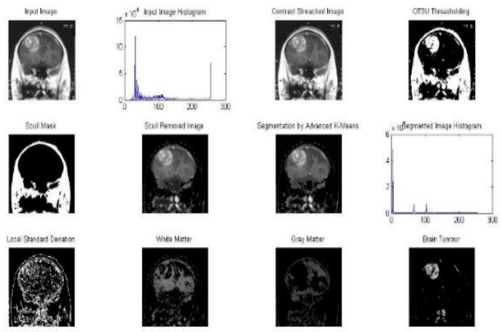

Scull Removed


K-Means O/P


White matter


Gray Matter


Tumor and dimension



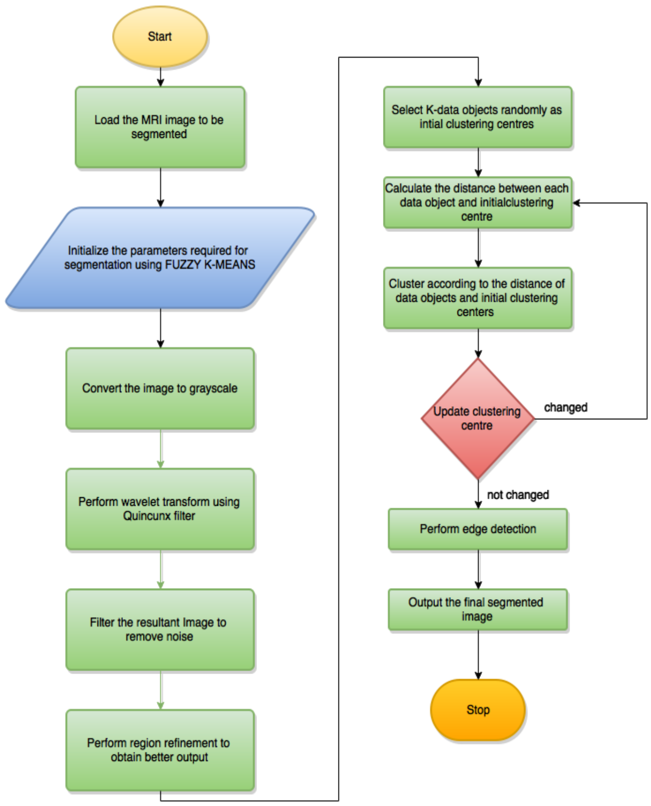
Histograms

SEGMENTATION USING WAVELET BASED FUZZY-K- MEANS TECHNIQUE

Segmentation of an image may be done using various techniques such as edge-detection technique, thresholding technique, region based technique, clustering technique, neural network technique. The method of segmentation which involves classification of objects into certain groups or clusters depending on some of the specific properties of the objects is known as clustering. In this technique, initially an attempt is made to extract a vector from the local areas of the image. The standard way of clustering is to assign each pixel to the nearest cluster mean. We can classify clustering algorithm into k- means clustering, hard clustering, fuzzy clustering, etc.

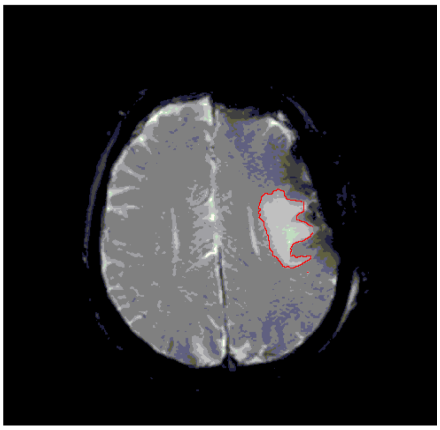
An example of hard-clustering algorithm is the k-means one (abbreviated as HCM). This process needs a value of either 1 or 0 to every patterned data. Then an 'initial hard c-partition' is given to it, that is, the c center is evaluated and each object is connected to the centre those are nearest to it to reduce the within-cluster variance. After every iteration it performs a test which compares the present partition with the previous one, and if it finds that the difference is less than a predefined threshold, the iteration will stop or else it will continue. K-means algorithm is statistical clustering algorithm. K-means algorithm depends on the index of similarity or dissimilarity between various pairs of data components. This algorithm is quite popular for its simple nature and ease of implementation and it is widely used to group pixels in the image.

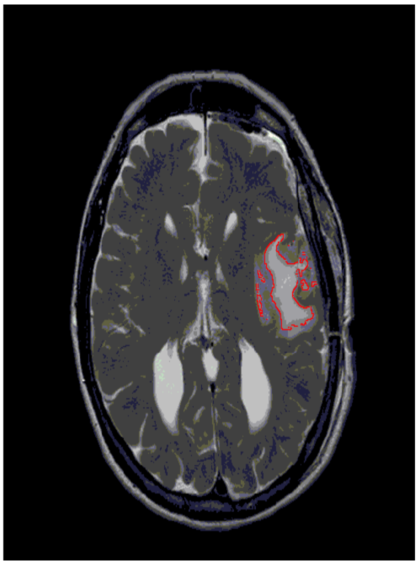
On the other hand fuzzy clustering method is a type of clustering algorithm which depicts the relationship between the input data pattern and clusters more naturally. Fuzzy c-means is one of the most popular fuzzy-clustering methods whose effectiveness is largely limited to spherical clusters. Both these techniques have their own disadvantages as well as advantages. So we have combined the plus points of both the algorithms to create a more powerful algorithm which is known as the Wavelet based Fuzzy K-means algorithm.



Output

Some of the segmented images, which are the outputs of our algorithm, have been shown below. *The segmented part is bounded by the red border*.





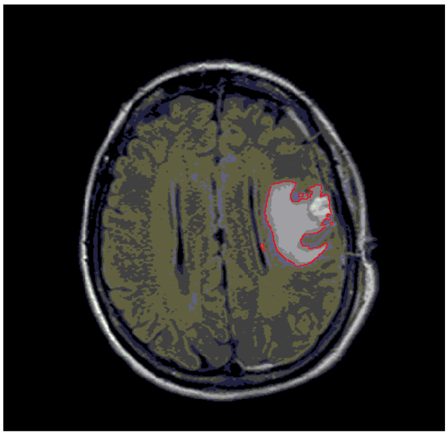
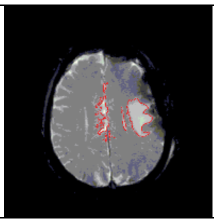
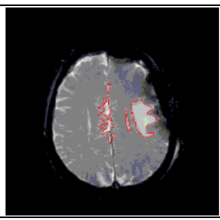
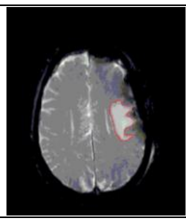
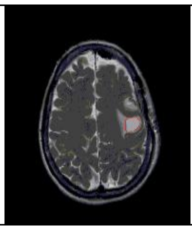
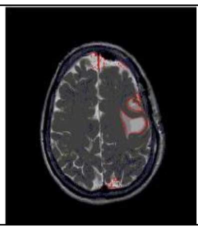
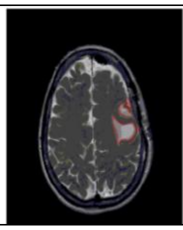
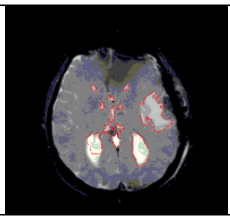
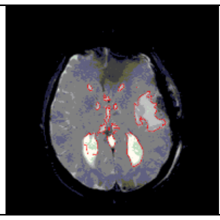
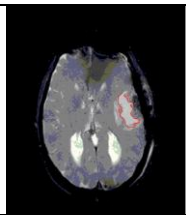
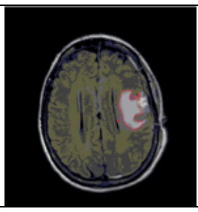
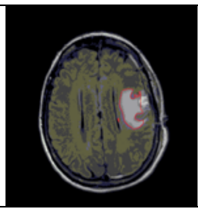
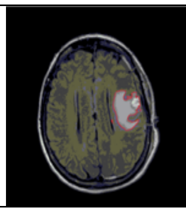


Table 1: Comparison of Outputs of traditional segmentation algorithms with our wavelet based Fuzzy K-means Algorithm[16], [17]

Output	Fuzzy C-means	K-means	Wavelet based Fuzzy K-means
Output 1			
Time taken	4.891sec	5.662sec	6.823 sec
Output 2			
Time taken	5.141sec	5.679sec	6.596 sec
Output 3			
Time taken	4.797sec	5.312sec	6.231 sec

Output 4			
Time taken	4.912sec	5.892sec	6.927 sec

CONCLUSION

Working with multiple MRI images reduces the noise automatically as well as reduces the chance of imaging error effecting the segmentation result. Moreover, fusing of multiple images results in high quality image and thereby produces high precision result. The registration needs to be accurate because, false registration will give incorrect segmentation result. The fusing technique is implemented by varying the alpha factor. Other more sophisticated state of the art methods could be used for better image fusion in future. The segmentation algorithm is the same earlier proposed method of advanced K – means algorithm with dual localization method thereby giving satisfactory result. Since due to multiple image fusion, the resultant image is of high quality, so the segmentation algorithm gives results with high precision. Wavelet based segmentation using Fuzzy- k-means clustering algorithm is facile to implement and only requires the number of clusters once for the given data points. Our outcomes revealed that our algorithm can improve the normal k-means algorithm. Efficiency is attained because the sample points do not vary throughout the computation and, hence, this data structure does not need to be recomputed at each stage. Our approach varies from existing algorithms only in how closest centers are computed with accuracy. We have demonstrated the practical efficiency of this algorithm both theoretically, through a data sensitive analysis, and empirically, through experiments on both synthetically generated and real data sets. The outcomes for both synthetic and real data sets stipulate that our proposed algorithm is notably more productive than the other two methods that were proposed previously. The progress of a simple and well organized algorithm which blends the best elements of the kinetic and filtering approaches would make a consequential offering.

REFERENCES

1. Chang PL, Teng WG Exploiting the self-organizing map for medical image segmentation. In: Twentieth IEEE international symposium on computer-based medical systems, 2007; 281–288.
2. Zhang Y et al A novel medical image segmentation method using dynamic programming. In: International conference on medical information visualisation-bio Medical visualisation, 2007; 69–74.
3. Hall LO, Bensaid AM, Clarke LP, Velthuizen RP, Silbiger MS, Bezdek J A comparison of neural network and fuzzy clustering techniques in segmenting magnetic resonance images of the brain. IEEE Trans Neural Netw, 1992; 3: 672–682.
4. Tian D, Fan L A brain MR images segmentation method based on SOM neural network. In: The 1st international conference on bioinformatics and biomedical engineering, 2007; 686–689.
5. Han X, Fischl B Atlas renormalization for improved brain MR image segmentation across scanner platforms. IEEE Trans Med Imaging, 2007; 26(4): 479–486.
6. Dunn, J.C.," A fuzzy relative of the ISODATA process and its use in detecting compact, well Separated clusters", Journal of Cybernetics, 1973; 3: 32-15.
7. sai. C, Manjunath B.S, Jagadeesan. R,:" Automated Segmentation of brain MR Images", Pergamon, Pattern Recognition, March 1995; 28(12).
8. Bezdek, J.C., "Cluster validity with fuzzysets", Cybernetics, 1974; 3: 58-73.
9. Ruspini, E., "Numerical methods for fuzzy clustering", Information Sciences, 1970; 2: 319-350.
10. Kannan S.R,:" Segmentation of MRI Using New Unsupervised Fuzzy C mean Algorithm", ICGST, 2005.
11. Jayaram K. Udupa, Punam K. Saha,:" Fuzzy Connectedness and Image Segmentation", Proceedings of the IEEE, Oct 2003; 91(10).
12. Vaidyanathan M, Clarke L.P, Velthuizen R.P, Phuphanich S, Bensaid A.M, Hall L.O, Bezdek J.C, Greenberg H, Trotti A, Silbiger ,:"Comparison of Supervised MRI Segmentation methods for Tumor Volume Determination During Therapy", Pergamon, Magnetic Resonance Imaging, 1995; 13(5): 719-728.
13. S. Murugavalli1, V. Rajamani," "A high speed parallel fuzzy c-mean algorithm for brain tumor segmentation", BIME Journal, Dec., 2006; (06) (1).
14. S. Murugavalli1, V. Rajamani," An Improved Implementation of Brain Tumor Detection Using Segmentation Based on Neuro Fuzzy Technique" Journal of Computer Science, 2007; 3(11): 841-846.
15. Parra, C.A., K. Iftekharuddin and R. Kozma, 2003." Automated Brain Tumor segmentation and pattern recognition using ANN", Computational Intelligence Robotics and Autonomous Systems.
16. Aidyanathan M, Clarke L.P, Velthuizen R.P, Phuphanich S, Bensaid A.M, Hall L.O, Bezdek J.C, Greenberg H, Trotti A, Silbiger M,:" Comparison of Supervised MRI Segmentation methods for Tumor Volume Determination During Therapy", Pergamon, Magnetic Resonance Imaging, 1995; 13(5): 719-728.
17. Chunyan Jiang, Xinhua Zhang, Wanjun Huang, Christoph Meinel.:" Segmentation and

Quantification of Brain Tumor," IEEE International conference on Virtual Environment, Human-Computer interfaces and Measurement Systems, USA, July 2008; 12-14.

18. Han Shen, William Sandham, Malcolm Granet, Annette Sterr.:" MRI Fuzzy Segmentation of Brain Tissue Using Neighbourhood Attraction with Neural-Network Optimization", IEEE Transcations on Information Technology in Biomedicine, Sep 2005; 9(3).
19. Hillips, W.E, Velthuizen R.P, Phuphanich S, L.O, Clarke L.P, Silbiger,:" Application of fuzzy C-Means Segmentation Technique for tissue Differentlation in MR Images of a hemorrhagic Glioblastoma Multiforme ", Pergamon, Megnetic Resonance Imaging, 1995; 13.
20. Kohonen. T "The self-organizing map". Proceedings of the IEEE, 1990; 78(9): 1464–1480.
21. Pal, N.R. and S.K. Pal," A review on image segmentation techniques", Pattern Recognition, 1993; 26(9): 1277-1294.
22. Phillips, W.E, Velthuizen R.P, Phuphanich S, L.O, Clarke L.P, Silbiger,:" Application of fuzzy C-Means Segmentation Techniquefor tissue Differentlation in MR Images of a hemorrhagic Glioblastoma Multiforme ", Pergamon, Megnetic Resonance Imaging, 1995; 13.
23. Squire LF, Novelline RA (1997). Squire's fundamentals of radiology (5th ed.) Harvard University Press.
24. Linda G. Shapiro and George C. Stockman (2001): "Computer Vision", 279-325, New Jersey, Prentice-Hall.
25. S. Wareld, J. Dengler, J. Zaers, C. Guttmann, W. Gil, J. Ettinger, J. Hiller, and R. Kikinis. "*Automatic identication of grey matter structures from mri to improve the segmentation of white matter lesions*". J. of Image Guided Surgery, 1995; 1(6): 326{338}.
26. M. Sezgin and B. Sankur "Survey over image thresholding techniques and quantitative performance evaluation". Journal of Electronic Imaging, 2004; 13(1): 146–165.
27. Nobuyuki Otsu "A threshold selection method from gray-level histograms". IEEE Trans. Sys., Man., Cyber., 1979; 9(1): 62–66.
28. J. B. MacQueen "Some Methods for classification and Analysis of Multivariate Observations, Proceedings of 5-th Berkeley Symposium on Mathematical Statistics and Probability", Berkeley, University of California Press, 1967; 1: 281-297.