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Enhancement Techniques and Methods for MRI-A Review

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***Abstract*— In this review paper, it is planned to review and compare the different methods of diagnosing brain tumor through MRI used in preprocessing and segmentation techniques. In preprocessing and enhancement stage is used to eliminate the noise and high frequency components from MRI image. In this paper, various Preprocessing and Enhancement Technique, Segmentation Algorithm and their performance have been studied and compared.**

***Keywords*— Pre-processing, Medical Imaging, Tumors, Morphological Operators, Image segmentation; Modified Tracking Algorithm; Center Weighted Median (CWM) Filter**.

I. INTRODUCTION

It organize a Multimodal Brain Tumor Segmentation (BRATS) is Medical Image Computing and Computer Assisted Intervention (MICCAI) challenged. Patient diagnosis of medical image is very important. To goal provide a about overview by giving a brief to brain tumors and brain tumor of image. Medical imaging is an essential component for application in the medical track of events including clinical diagnostic settings, planning, consummation, and evaluation of surgical procedures. The computer-aided diagnosis system (CAD) is used for clinical diagnosis and treatment.

Brain tumors are affected most common cause of cancer death in women. The most common primary cancers that distribute to the brain are lung, breast, unknown primary, melanoma, and cancer [79].Advantage of MRI is that soft tissue contrast is good, especially in brain and spinal cord scans. The aim of the segmentation is outline the tumor including its subcommittee and surrounding tissues and main task in registration and modeling is the handling of morphological changes caused by the tumor.

Classify the brain tumors grades I–IV. High-grade tumor is grade III or IV. Grades I and II tumors may be considered as normal tissues tumor, after remove the cancers and grades III and IV tumors are very dancer grade because certainly subject is death.

II. IMAGE ACQUISITION

To access the real medical images for carrying out research is a very difficult because of privacy issues and heavy technical difficult. This idea is automatic brain tumor detection methods through MR brain Images. A sample of 80 T1 weighted images is used for enhancement purpose. T1- weighted images visible water darker and the fat brighter. All MR images were acquired on a 0.5T open prevent tumor MRI system [2]. Most Medical Imaging Studies and detection are directed using MRI, Positron Emission Tomography (PET) and Computed tomography (CT) Scan.

Figure.1: Sample of brain images

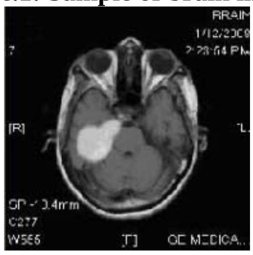

Figure.2: Acquired brain images

III. PREPROCESSING TECHNIQUES

A. Removal of film artifacts

The MRI brain image consists of film artifacts or label on the MRI include patient name, age and marks. Modify tracking algorithm used to eliminate film artifact. This algorithm analysis the brain tumor of image the first row and first column is started, the intensity value of the pixels are analyzed and found the threshold value of the film artifact. Center weighted median filter used to film artifacts are removed from MRI brain image.

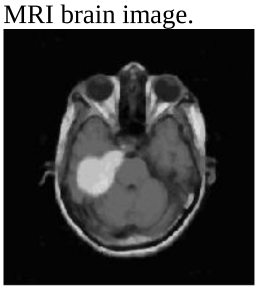

Figure 3. Removal of film artifacts

B. Removal of Skull using Modified Tracking Algorithm

To eliminate unwanted portion of MRI by using modified Tracking Algorithm. The MRI brain tumor image is left, right and top skull portions. To obtain finally eliminating the film artifacts and labels is taken. Brain tumor of image is started from first row, first column of left the given matrix and select the peak threshold value from matrix of left side and considers the 200 flag value. [85]

C. Need for pre-processing

The pre-processing is required for MRI images as:

- Marks or labels present (Film artifacts) can prevent in the post-processing of these images.
- Images are to be made more suitable for advanced processing in CAD systems.
- Enhance the quality of image.
- Remove the noise of image.

Preprocessing is used to displaying the digital images or highlighting edges of image. The Preprocessing Techniques include the Content Based model, Fiber tracking Method, Wavelets & Wavelet Packets, and Fourier transform technique [81; 82; 83; 84].

TABLE I
AN OVERVIEW OF PREPROCESSING METHODS

Methods	Remarks
Neural Networks, Genetic Programming[86]	Data is large volume the processed successfully.
Pixel Histograms, Morphological Process [87]	It removes the noise and it can improve the integrity performance**.**
Boundary Model ,Nonlinear matching scheme[88]	It represents the idealized MR intensity profile accurately.
PCA (Principal Component Analysis)[89]	To reduce the artifacts present in the PET data set.
Boundary Detection Algorithm, Generalized Fuzzy operator(GFO),Contour Deformable Model, Region base technique[90]	To find result in the tumor consideration.
Head Model, Finite Difference Time-Domain (FDTD)[91]	It is used to analyze the more type of tissue. .
Fiber tracking Method, Runge-Kutta method[84]	The satisfied of MR-DT1 datasets
Geometric prior, Bimodal[7]	It is use to image of registered.

IV. ENHANCEMENT

Image enhancement techniques used to develop the visual appearance of images from Magnetic Resonance Image (MRI) and the enhancing brain volumes were aligned linear and this image is contrast. The enhancement operate are eliminate of film artifacts and labels, filtering of images. There are more number of enhancement techniques such as Median filter, Gabor Filter, Gaussian Filter, low pass filter and Prewitt edge-finding filter.

V. SEGMENTATION

Tumor brain image is very important task of segmentation and type of reasons .First step is g high grade of brain tumor usually exhibit irregular and unclear boundaries with discontinuities. Segmentation algorithms use the non-image able component of the tumor should be handled. It is used to separation of the brain tumor image into regions of similar attribute. The accurate segmentation of MRI image is tissue classes of different, especially gray matter, and Cerebrospinal fluid and white matter. The calculate the Regions of Interest (ROIs) in an image by segmentation. The digital image processing has developed more number of segmentation methods. Only four common methods are: first is amplitude thresholding, second is texture segmentation, third is template matching, and fourth is region-growing segmentation. These methods used for detecting tumors, edema and necrotic tissues. These types of segmentation algorithms are used to dividing the brain images into three categories. Several authors suggested various algorithms for segmentation [91].

A. Literature Survey

The image segmentation is a challenging problem that has received an enormous amount of attention by many researchers [1, 2, 3, and 4]. Phametal.And Jamesetal. Have presented various techniques used in medical image segmentation and analysis[5,6].The segmentation problem can be categorized as supervised and unsupervised problem. For appropriate analysis, different image models have been proposed for taking care of spatial intrinsic characteristics.

The popular stochastic model provides the better framework for many complex problems in image segmentation is Markov Random Field (MRF) model [7, 10]. MRF model and its variants have been successfully used for brain MR image segmentation [12, 13]. Ruan et al. proposed a fuzzy Markova method for brain tissue segmentation from magnetic resonance images that calculates a fuzzy membership in each pixel to indicate the partial volume degree, which is statistically modeled [14].

In unsupervised framework, the more number of class labels and assumed model parameters to be unknown. Hence, estimation of image labels and model parameters are required simultaneously. Since, the image label estimation depends upon the optimal set of parameters, the segmentation problem can be viewed as incomplete data problem. To handle this problem, an iterative scheme, named Expectation-Maximization algorithm has been proposed [16].

Zhang et al. Proposed Hidden Markov Random Field (HMRF) model to achieve brain MR image segmentation in unsupervised framework [17]. The segmentation obtained by Zhang's approach greatly depends upon the proper choice of initial model parameters. As Expectation-Maximization algorithm yield solutions at the cost of high computational burden, in order to overcome this Marroquin et al. have proposed a new class of probabilistic model, called Hidden Markov Measure Field model that solved the complex segmentation problem by minimization of differentiable energy function [18]. Wellsetal. And Bradyetal .have proposed an adaptive brain MR image segmentation scheme in EM framework [19,20].They have also taken spatial intensity in-homogeneity into account and Have estimated the bias field. Recently Hung et al. proposed an automatic segmentation method based on a decision tree to different classes the brain tissues in magnetic resonance (MR) images [22].

Guanetal. have proposed an automatic hotspot detection and segmentation of whole body PET images using threshold and the Hidden Markov Model(HMM).They compare the fixed PET pixel data threshold and the fixed standard up take values(SUV) threshold for segmenting hotspots[24]. Nanda etal proposed a Tabu search based unsupervised scheme using HMRF-EM framework which could segment the images properly taking arbitrary initial parameter [25]. Anand etal .transformed an true image into a domain of multi scale wavelet and the wavelet coefficients are processed by a soft thresholding method.

Various wavelet filter based denoising methods are studied according to different thresholding values and applied to ultrasound images [23].Joshi etal. Modeled the fused multispectral (MS) image using a low spatial resolution MS images as the aliased and corresponding noisy versions as high spatial resolution. The fused image is obtained for each of the MS bands by estimating the high spatial resolution and then modeling as separate inhomogeneous Gaussian Markov random fields (IGMRF) and a maximum a posteriori (MAP) estimation [26].

Nowadays, fuzzy image segmentation is increasing popularity because of rapid extension of fuzzy set theory, the development of various fuzzy set based mathematical modeling, and it successful application in computer vision system [27]. Ichihashi et al. showed that the EM algorithm for GMM can be derived from the FCM type clustering, when considering a regularization by KL information fuzzy objective function, for selection of the distance metric[28].Ahmed et al. Fuzzy c-means algorithm proposed a bias correction in which they incorporated a neighborhood regularize into the FCM objective operation to allow labeling of a pixel to be influenced by the labels in its immediate neighborhood of label [29].

Incorporating the spatial neighborhood information into the FCM algorithm standard and modifying the membership weighting of each cluster using the algorithm. Parui et al. Approached a mixture model suitable for segmentation of the color images. The certain color space in a pixel is clustered by employing the K-Means algorithm[30].A General Reflex Fuzzy Min-Max Neural Network (GRFMN)is to extract the underlying structure of the data by means of supervised ,unsupervised and partially supervised learning is proposed by Biswas etal. [31]. Chen et al. Proposed an adaptive FCM algorithm which is found to be robust in convergence. The proposed function to be minimized has regularization terms that

Ensure the estimated bias field is smooth and slowly varying [32]. Siyal et al. Presented a modified FCM algorithm formulated by modifying the objective function of the standard FCM and uses a special spread method for classification of tissues [33].

Wang et al. Proposed a modified FCM algorithm, called MFCM for brain MR image segmentation [34]. Aboulella et al. Proposed a statistical feature extraction technique for diagnosis of breast cancer mammograms by combining the fuzzy image processing with rough set theory [35]. Martin et al. Described away to segment the medical images using an appropriately defined fuzzy clustering based on a fuzzy relation. The considered relation is defined in terms of Euclidian distance [36]. Kang et al. Presented an ovel method for segmentation by incorporating spatial neighborhood information in to the standard FCM.

An adaptive weighted averaging filter is given to indicate the spatial influence of the center pixel [37].Panas et al. Proposed the Adaptive Fuzzy Clustering/Segmentation (AFCS).In AFCS, then on-stationary nature of the taken the image in account using modifying the prototype vectors as function of sample location in the image. A multimodal is utilized for varies of estimating the spatially prototype vectors for different window sizes. The results provide segmentation having lower entropy [38].Mohamed et al. described the application of fuzzy set theory in medical imaging.

To obtain cluster is proposed of fully automatic technique. A modified fuzzy c-means classification algorithm is by to provide a fuzzy partition. The method is inspired by Markov random field (MRF) and to be less sensitive to noise found as it filters the image while clustering [39]. Karnan et al. presented a new method called Fuzzy Membership C-Means(FMCM) for segmentation of Magnetic Resonance Images(MRI).This work develops the construct the initial membership matrix to clusters into improve the strength of the clusters [40].

TABLE II A SURVEY OF SEGMENTATION METHODS

Methods	Remarks
LindeBuzo-Gray algorithm method [42]	Linde Buzo-Gray algorithm (LBG) used for segmentation of MRI images.
Atlas registration and pattern recognition [43]	To PET attenuation correction (AC), used two algorithms for whole-body MRI-based AC (MRAC) based on atlas registration and pattern recognition (AT&PR)
Scanning segmentation [44]	To optimize automated image segmentation performance possible to shorter scanning times and better image.
Segmentation and registration [45]	DWI-MRI image sequences of the liver tested of different patient by aligning and computing ADC maps. Five different DWI sequences (b=0, 50,250,350,500) of each scan.
Attenuation-Correction method [46]	AC entirely on the MRI data obtained and used for neurologic performed with the MR-PET human brain scanner prototype.
Kekre'sFast Codebook Generation (KFCG) [47]	Generation (KFCG) algorithm used for segmentation of the entropy image.
Artificial Bee Colony (ABC) algorithm [48]	To improve the efficiency of FCM on abnormal brain images by Artificial Bee Colony (ABC) algorithm.
T2-weighted (T2W) MRI and proton density weighted MRI [49]	Evaluates the possibility of using proton density weighted (PDW) MRI to improve the definition of titanium tandems.
SSVM[50]	SSVM are the two classification models, to segment the internal lumen wall of carotid artery. The better results show the segmentation performance of SSVM.

Methods	Remarks
clustering method [51]	Clustering method to provide the advantage of improvement of computational time over fuzzy c means approached. Segmentation accuracy is slighter lower than fuzzy c means.
Distance Regularized Level Set Evolution[52]	DRLSE allows efficient initialization of the level set function used. To reduce the more number of iterations, sufficient-numerical accuracy can be used. Provide reduce computational cost.
Unsupervised MR image segmentation method [53]	Fuzzy C-mean clustering algorithm for Segmentation is presented.
vector quantization techniques.[54]	Proposed for performing segmentations depends on the application, imaging modality, and other factors.
Ultra short-Echo-Time/ Dixon MRI sequence [55]	To separate cortical bone and air, the Dixon technique for soft and adipose tissues are used.
Biomedical and anatomical information (56)	To obtain the success results of automating image segmentation is achieved. It has enhance the image.
Gaussian Mixture Model[57]	It used to efficiently pixels of image as belonging to either the low-intensity or high-intensity background of image.
Markov Chain Monte Carlo methods[58]	It used distributions simulated image and detection based on model checking techniques Bayesian mixture model using segmentation algorithm.
MPR nanoparticle [59]	It used to accurately help the delineate the tumors of margins in living both preoperatively and intra operative.
Local region-based active contour models[60]	It suitable to MRI brain image and It can find the tumor-dominant slice, contour automatically and segment tumor's contours.
Bacteria Foraging Optimization Algorithm[61]	To obtain the image pixel data and merge of region/neighborhood map to form a context of image.
Hierarchical Self Organizing Map (HSOM)[62]	To achieve lowest value of weight vector, a highest value of tumor pixels, computation speed. It's used to classify the brain tumor of MRI image.
Hybrid Parallel Ant Colony Optimization (HPACO)[63]	It used to optimum label is determined that Maximizing a Posterior (MAP) minimize the estimate to segment the image.
Self-Organizing Map (SOM) algorithm[64]	To eliminate film artifact and noise and to accurately identify of image segmentation.
Integrating fuzzy-c-mean (FCM)[65]	To correct the brain tumor of images, and to detect the midline position of the brain.
positron emission tomography (MR/PET)[66]	To remove the skull on MR images for attenuation correction of brain image MR/PET applications.
Hippocampal Volumetry (HV)[67]	It's used to more accurate of MRI analysis and the image is highest classification accuracy is determined.
MR spectroscopy method[68]	To obtain metabolites, neurons of specific, glial cells, are altered of images.

Methods	Remarks
Ultra-high field 7 tesla (T) MRI [69].	It used to visualize and segment of images and high contrast.
Bilateral filtering[70]	To acquire critical features from MRI images. it create the effective and efficient of segment of image.
Alzheimer's disease (AD) and front temporal dementia (FTD)[71]	To assess brain gray (GM) and white matter (WM) abnormalities jointly between the disease to elucidate differences in abnormal MRI image.
SNAP software[72]	To manually segmented in the axial, sagittal, and coronal planes. The brain tumor image is P5,P14, and P72 atlases had 39, 45, and 29 regions segmented.
SOM-FCM-Based Method and 3D Statistical.[73]	it using 3D statistical features extracted from the brain tumor image are proposed.
Dopaminergic System[74]	To achieve the high-resolution T2- and T2*-weighted GRASE and performed 7T FFE MR imaging scan.
Ant Colony System[75]	To Segment the region is extracted of image and the measure radiologist report from tumor position and pixel similarity of the ACS.
Momestic pig method[76]	To develop and validate MRI methods for estimating brain volume of image.
Maximum probability pediatric atlas (MPPA)[78]	To comparing with manual segmentations by the Dice overlap coefficient. z0.90 ± 0.03 for the hippocampus, 0.92 ± 0.01 for the caudate nucleus and 0.92 ± 0.02 for the pre-central gyrus.

VI. CENTER WEIGHTED MEDIAN FILTER

Median filter is used to eliminate the noise and high frequency components from MRI image. and reduce' salt and pepper' noise and without disturbing the edges. A median is calculated by all pixel values sorted by their size, then selecting the new value as median value for the pixel. The amount of 3*3 window pixels should be used to calculate the median [92]. A weighted median filter used for removing noise from MRI brain images with contrast. It has a great potential for being used in rank order filtering and image processing. The Center Weighted Median (CWM) filter, is a weighted median filter .it uses to weight of value of each window. This filter can preserve image details while suppressing additive white and/or impulsive-type noise. The statistical properties of the CWM filter are analyzed.

VII. CONCLUSIONS

In this survey paper, various method of brain tumor through MRI are studied and compared for preprocessing and segmentation techniques. It is used to give large information about brain tumor segmentation and detection and milestones for analyze from different MRI medical image processing. In this paper, various steps in Preprocessing and Enhancement Technique, Segmentation Algorithm and their performance have been studied and compared.

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