A Survey of Recent Image Segmentation Techniques for MRI Brain Images

[1]S. Valarmathy, [2]R. Ramani, [3]Dr. N. Suthanthira Vanitha
[1,2]Anna University, Coimbatore, Tamilnadu, India
[3]Dept. of EEE, Kiot, Salem, Tamilnadu, India

Abstract
The brain tumor detection from Magnetic Resonance Images (MRI) is one of the mainly challenging tasks in Medical imaging techniques. MRI used to produce images of soft tissue of the human body, used to analyze the human organs without any surgery. The purpose of segmentation is to simplify and change the representation of an image into meaningful image to analyze. The image segmentation is a very difficult job in the image processing and challenging task for clinical diagnostic tools. Noises present in the Brain MRI images are multiplicative noises and reductions of these noises are difficult task. There are many noise reduction techniques available to cut the noises from brain images to detect tumor or cancer. Accurate segmentation of the MRI images is extremely important and essential for the exact diagnosis by computer aided clinical tools. This paper is to check existing approaches of preprocessing and current segmentation techniques in brain images. The aim of preprocessing is to improve the image quality, removing the irrelevant noises and unwanted parts in the background of the MRI images. There are different types of segmentation algorithms for MRI brain images. Their advantages and disadvantages discussed.

Keywords
MRI Images, Image Segmentation, Preprocessing, FCM, MKFCM

I. Introduction
Magnetic Resonance Images used in the biomedical to detect and visualize finer details in the internal structure of the body. This technique used to detect the differences in the tissues that have a far better technique as compared to other techniques. Therefore, this makes this technique a very special one for the brain tumor detection and cancer imaging [1].

Each year, more than 190,000 people in the United States and 10,000 people in Canada diagnosed with a brain tumor. Of these, over 40,000 are primary brain tumors. In the United States, the overall incidence of all primary brain tumors is 14.1 per 100,000 people per year. Primary brain tumors are the leading cause of solid tumor cancer deaths in children under the age of 20, now surpassing Acute Lymphoblast Leukemia (ALL), and are the third leading cause of cancer death in young adults ages 20-39. Although as many as 70% of children diagnosed with primary brain tumors will survive, they are often left with long-term side effects. Over 150,000 secondary ("metastatic") brain tumors occur yearly in the United States. Secondary brain tumors occur at some point in 10-15% of people with cancer [2]. This year, an estimated 22,910 adults (12,630 men and 10,280 women) in the United States will be diagnosed with primary malignant tumors of the brain and spinal cord. It has estimated that 13,700 adults (7,720 men and 5,980 women) will die from this disease this year. Brain tumors are the tenth most common cause of cancer death in women [3]. Prevalence of primary brain tumors estimated at 221.8 per 100,000 people in 2010, compared with 209 per 100,000 in 2004. Primary brain and CNS tumors originate in the brain or spinal cord, as opposed to metastatic tumors that originate elsewhere and spread to the brain or spinal cord. In 2012, an estimated 66,290 new primary brain tumor diagnoses will be made in the U.S., 24,300 malignant and 41,980 nonmalignant. An estimated 13,700 deaths are expected to occur this year due to brain tumors, 7,720 males, and 5,980 females [4].

The National Brain Tumor Foundation (NBTF) for research in the United States estimates the death of 13000 patients while 29000 undergo primary brain tumor diagnosis every year [5]. Depending on the origin and growth, brain tumor classified into two types: 1) primary brain tumor developed at the original site of the tumor 2) secondary brain tumor is the cancer that spreads to the other parts of the body. The detection of brain tissue and tumor in MR images and CT scan images has been an active research area [6]. Segmenting and detection of specific regions of the brain containing the tumor cells considered the fundamental problem in image analysis related to tumor detection.

Image segmentation is a central task in many research fields including computer vision [7] and intelligent image and video analysis [8]. Its essential goal is to split the pixels of an image into a set of regions, such that the pixels in the same region are homogeneous according to some properties and the pixels in different regions are not similar. Brain image segmentation from MRI images is problematical and challenging, but its precise and precise segmentation is necessary for tumors detection and their classification. For early detection of abnormalities in brain image 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 [9]. Therefore, MRI image segmentation stands in the upcoming research in medical imaging.

A variety of image segmentation techniques available for MRI brain images introduced to make the segmentation more effective. In this paper, we have reviewed of the recent preprocessing and image segmentation techniques for MRI brain images.

II. Pre-Processing
Today MRI brain cancer or tumor detection is very important role for worldwide to save the life. Doctors and radiologistic can miss the abnormality due to inexperience in the field of cancer or tumor detection. The pre-processing is the most important step in MRI brain image analysis due to poor captured image quality. Pre-processing is necessarily for to correct and adjust the image for further study and processing. Different types of filtering techniques are available for pre-processing. These filters normally used to improve the image quality, suppress the noise, preserves the edges in an image, enhance and smoothen the image. we have used various filters namely, median filter, adaptive median filter, average or mean filter, and wiener filter used for MRI brain image pre-processing. From this observation median filter is better while compare with other filters.

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III. Image Segmentation

The main objective of image segmentation is to extract various features of the images that may merge or split in order to build objects of interest on which analysis and interpretations performed.

Image segmentation refers to the process of partitioning an image into groups of pixels that are homogeneous with respect to some criterion. The result of segmentation is the splitting up of the image into connected areas. Thus, segment is concerned with dividing an image into meaningful regions. The image segmentation techniques such as Detection of Brain Tumor based on Wavelet Based Image Fusion, Fuzzy Symmetry Based Genetic Clustering Technique, Wavelet and FCM Algorithm, Random walk, Modified Kernelized Fuzzy C-Means, Multiple kernel fuzzy c-means, Neural Network used for image segmentation.

1. Detection of Brain Tumor based on Wavelet Based Image Fusion

In [10], wavelets based image fusion algorithm applied to the Magnetic Resonance (MR) images and Computed Tomography (CT) images,used as primary sources to extract the redundant and later information to enhance the brain tumor detection in the resultant fused image. The features taken into account to detect the brain tumor place and size of the tumor, which is more optimized through fusion of images by a variety of wavelets transforms parameters. The performance of the algorithm evaluated based on PSNR values. Wavelets analysis widely used method for solving difficult problems in engineering in the present times. Wavelets transforms is a new area of tools, replacing the Fourier transform in a mixture of fields of application like image processing, heart-rate and ECG, DNA analysis, general signal processing, speech recognition, computer graphics [8]. In this paper, an image Fusion technique effectively used to detect the tumor in a mixture of complex backgrounds. Image Fusions applied by merging multiple images resulting into precise information about the size, shape and placement of the tumor. Before applying image fusion, the source images preprocessing through various Image enhancement techniques.

In this method, mask operations used for the enhancement of the images. These techniques improve the efficiency of the image fusion algorithm through elimination of ambient elements from MRI images. The wavelet transform applied on the source images with different wavelets such as Daubechies, Symlets, and Coiflets in order to obtain optimum results. Fusion performed either by taking the average of the coefficients either the minimum of the coefficients or maximum of the coefficients. The wavelet transform technique of the image fusion allows effectively extract the salient features of the input images and produced better results than Laplacian pyramid based methods. This method provided better detection of the tumor with minimum error. The first level decomposition used in the proposed method and results analyzed by varying the other two parameters in order to get optimum results. The efficiency of the proposed method compared with some standard algorithms like GVF and segmentation. The proposed method provided an accurate and computationally efficient method for detection of brain tumor through wavelet based image fusion.

2. Fuzzy Symmetry Based Genetic Clustering Technique for MRI Brain Image Segmentation

In [11], the proposed an automatic segmentation technique of multispectral image of the brain using a fuzzy symmetry based on genetic clustering. A developed fuzzy point symmetry based cluster validity index, fuzzy symmetry index, used to measure of ‘goodness’ of the corresponding partition. The genetic fuzzy clustering technique to evolve the number of clusters present in the data set automatically. The proposed method better while compare with Fuzzy C-means. This method does not require any priority specification of the number of clusters present in the data set. The obtained results compared with the available ground truth information. This method fully automatically segment the brain image and the membership values of points to different clusters computed based on proposed point symmetry based distance than the Euclidean distance. This method is used to automatically develop the proper clustering of all types of clusters, both convex and non-convex, which have some symmetrical structures.

3. Wavelet and FCM Algorithm for MRI Brain Image Segmentation

In [12], Fuzzy C-Means (FCM) Clustering and wavelet Decomposition for the feature extraction and feature vector treat as input to FCM. This method is called as Wavelet Fuzzy C- means (WFCM). This method used to segment MRI brain images. Two stages involved in the proposed method, one is feature extraction and other is clustering. The feature extraction processed by using multilevel 2D wavelet decomposition features. . To obtain the wavelet features, here Daubechies-4(DAUB4) wavelets applied to the image and performed a two level wavelet transform. Feature extraction from wavelet decomposition given to Fuzzy C-Means, FCM applied on the feature vector obtained from previous step for clustering. The output image segmented into three classes (WM, GM, and CSF). The wavelet Fuzzy C- Means (WFCM) algorithms implemented by Mat lab (2010b), and tested on two MRI databases.

4. Random Walk MRI Brain Image Segmentation

The random walk algorithm used for medical image processing segmentation to detect cancer cells in breast or brain images. Random walk defined as discrete random motion in which a particle repeatedly moves a fixed distance up, down, east south, and north, this is a region growing based image segmentation method based on random walk of a particle. In this method, the initial position at which a particle is initially present known as seed point movement from one position to another method based on the probability calculations. In this method, three pragmatic properties of random walk algorithm, weak boundary detection, noise robustness and the assignment of ambiguous regions. Seed point selection is very important for random walk, after the seed point has been detected random walk methods performed for segmentation and then fine segmented [13].

5. Modified Kernelized Fuzzy C-Means segmentation for MRI images

The Modified Kernelized Fuzzy C-Means (MKFCM) algorithm implemented for MRI image segmentation [14]. In KFCM directly applied to image segmentation like FCM. To modify the algorithm by taking into account the image topology. The Modified KFCM as follows.

- To initialize the cluster centers by “Expectation Maximization” (EM) algorithm [15] for an optimal choice of the centers.
- To take into account the image topology; the statistical parameters of a window around the pixel are considered.

For an image y, of size (N × M), and a sliding window of size (p × p), the four features extracted from the window centered at pixel (n, r) are given by the following equations:

$$M = \frac{1}{MN}\sum_{i=-\frac{p-1}{2}}^{\frac{p-1}{2}}\sum_{j=-\frac{p-1}{2}}^{\frac{p-1}{2}} y(n+1, r+j) \qquad (1)$$

$$Var = \frac{1}{MN}\sum_{i=-\frac{p-1}{2}}^{\frac{p-1}{2}}\sum_{j=-\frac{p-1}{2}}^{\frac{p-1}{2}} (y(n+1, r+j) - Me)^2 \qquad (2)$$

$$Skn = \frac{1}{MN}\sum_{i=-\frac{p-1}{2}}^{\frac{p-1}{2}}\sum_{j=-\frac{p-1}{2}}^{\frac{p-1}{2}} (y(n+1, r+j) - Me)^3 \qquad (3)$$

$$K = \frac{1}{MN}\sum_{i=-\frac{p-1}{2}}^{\frac{p-1}{2}}\sum_{j=-\frac{p-1}{2}}^{\frac{p-1}{2}} (y(n+1, r+j) - Me)^4 \qquad (4)$$

Where, M, Var, Skn and K, are the mean, the variance, the skewness, and the kurtosis respectively. Note that p must be odd for a window centered on each pixel. The obtained a matrix H that contains the extracted features MKFCM segmented the image into three classes corresponding to background, Grey Matter (GM) and White Matter (WM) and Cerebrospinal Fluid (CSF). MKFCM formed better results than FCM.

6. Level Set Method based MRI Image Segmentation in the Presence of Intensity Inhomogeneities

The most commonly used image segmentation algorithms are region-based and typically rely on the homogeneity of the image intensities in the regions of interest, which is often failing to give right segmentation results due to the intensity inhomogeneity. This paper proposed level set based bias corrected MRI images used to detect the cancer or tumor, which is able to deal with intensity inhomogeneities in the segmentation. This method is able to consecutively segment the image and calculate about the bias field, and the estimated bias field, used for intensity inhomogeneity, bias correction. After bias corrected image, threshold segmentation and morphology techniques applied to detect the cancer or tumor in MRI images with effective results.

In order to deal with intensity inhomogeneities in image segmentation, we formulate our method based on an image model that describes the composition of real-world images, in which intensity inhomogeneity is attributed to a component of an image. In this paper, we have considered the following multiplicative model of intensity inhomogeneity. From the physics of imaging in a variety of modalities (e.g. camera and MRI), an observed image can be modeled as

$I = bJ+n$

Where J is the true image, is the component that accounts for the intensity inhomogeneity, and n is additive noise. The component is referred to as a bias field. The true image J measures an intrinsic physical property of the objects being imaged, which is therefore assumed to be piecewise (approximately) constant. The bias field is assumed to be slowly varying. The additive noise n can be assumed to be zero-mean Gaussian noise. In this paper, we consider the image as a function I: Ω: R defined on a continuous domain. The assumptions about the true image J and the bias field b can be stated more specifically as follows:

(A1) The bias field is slowly varying, which implies that b can be well approximated by a constant in a neighborhood of each point in the image domain.

(A2) The true image J approximately takes N distinct constant Values C1… CN in disjoint regions, respectively, Ω1………ΩN where forms a partition of the image domain, i.e. and for based on the model in (4) and the assumptions A1 and A

The described local intensity clustering property indicates that the intensities in the neighborhood O_y can be classified into N clusters, with centers m_i~b(y) c_i, i=1,….,N. ; this allows us to apply the standard K-means clustering to classify these local intensities. Specifically, for the intensities I(X) in the neighborhood $O_{y,1}$, the K-means algorithm is an iterative process to minimize the clustering criterion [16], which can be written in a continuous form as

$$F_y = \sum_{i=1}^{N} \int_{O_y} |I(X) - m_I|^2 \; u_i(x)dx \qquad (5)$$

We can rewrite F_y as

$$F_y = \sum_{i=1}^{N} \int_{\Omega i \cap O_y} |I(X) - m_I|^2 \; dx \qquad (6)$$

Therefore, we define energy

$$\varepsilon \triangleq \int \varepsilon_y \, dy, \qquad (7)$$

i.e

$$\varepsilon \triangleq \int \left(\sum_{i=1}^{N} \int_{\Omega i} k(y-x)|I(x) - b(y)c_i|^2 \; dx \right) dy \qquad (8)$$

In this paper, we omit the domain Ω in the subscript of the integral symbol (as in the first integral above) if the integration is over the entire domain Ω the Image segmentation and bias field estimation can be performed by minimizing this energy with respect to the regions Ω_1……… Ω_N, constants C_1…C_N, and bias field b. the kernel function K is chosen as a truncated Gaussian function defined by

$$K(u) = \begin{cases} \frac{1}{a} e^{-\frac{|u|^2}{2\sigma^2}}, & for\ |u| \le 0 \\ 0, & otherwise \end{cases} \qquad (9)$$

Where is normalization constant the energy in (8) can be expressed as the following level set formulation?

$$\varepsilon = \int \left(\sum_{i=1}^{N} \int k(y-x)|I(x) - b(y)c_i|^2 \; M_i(\emptyset(x))dx \right) dy \qquad (10)$$

The estimated bias field can be used for intensity inhomogeneity correction or bias correction for MRI images. Given the estimated bias field, the bias corrected image is computed as the quotient I/b. To demonstrate the effectiveness of our method in simultaneous segmentation and bias field estimation, we applied it to three medical images with intensity inhomogeneities: an MR image of brain, an X-ray image of bones, and an ultrasound image of prostate. These images exhibit obvious intensity inhomogeneities. The ultrasound image is also corrupted with serious speckle noise. We applied a convolution with a Gaussian kernel to smooth the ultrasound image as a preprocessing step.

7. Multiple kernel fuzzy c-means (MKFC)

The fuzzy c-means is a popular soft clustering method; its effectiveness is mainly limited to spherical clusters. Applying kernel behavior, the kernel fuzzy c-means algorithm attempts to address this problem by mapping data with nonlinear relationships to correct feature spaces. Kernel combination, or choice, is critical for efficient kernel clustering. Regrettably, for most applications, and is not easy to find the right combination. In [17], multiple kernel fuzzy c-means (MKFC) algorithm implemented which extends the fuzzy c-means algorithm with a multiple kernel learning location. By incorporating multiple kernels and automatically adjusting the kernel weights, MKFC is more vulnerable to hopeless kernels and unrelated features. This makes the choice of kernels less crucial. In addition, show multiple kernel k-means (MKKM) to be a special case of MKFC. Experiments on both artificial and real-world data demonstrated the efficiency of multiple kernel fuzzy c-means algorithm [17].

The kernel based segmentation technique, particularly for images with small resolution and reduced contrast. The application of multiple or multiple kernels in the FKCM (fuzzy kernel c-means) has its advantages. In addition to the flexibility in selecting kernel functions, it also offers a new approach to join different information from multiple heterogeneous or homogeneous sources in the kernel space. Specifically, in image-segmentation problems, the input data engage properties of image pixels sometimes derived from very dissimilar sources. Therefore, it can define different kernel functions purposely for the intensity information and the texture information separately, and then combine these kernel functions and apply the composite kernel in MKFCM to obtain better image-segmentation results.

The general framework of MKFCM aims to minimize the objective function

$$Q = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m}\left\|\emptyset_{com}(x_j) - \emptyset_{com}(o_i)\right\|^2 \tag{11}$$

To enhance the Gaussian kernel based KFCM - F by adding a local information term in the objective function

$$Q = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m}\left(1 - K(x_j, o_i)\right) + \alpha\sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m}\left(1 - k(x_j, o_i)\right) \tag{12}$$

This implemented algorithm is easy to implement and provides soft clustering results that are immune to irrelevant, redundant, ineffective, and unreliable features or kernels. The merits of MKFCM based image segmentation is flexibility in selection and combination of the kernel functions. The different shapes and for different types of information, after combining the different kernels in the kernel space, there is no need to change the computation procedures of MKFCM, this is another advantages to reflect and fuse the image information from multiple heterogeneous or homogeneous sources [18].

8. Neural Network based Methods

Artificial Neural Networks (ANNs) developed for variety of applications such as function approximation, feature extraction, optimization, pattern recognition and classification. Mostly, they have developed for image enhancement, segmentation, registration, feature extraction, and object recognition. From the above applications, image segmentation is more important and a crucial step for high level image processing such as detection of tumors in medical images. Hopfield, Back Propagation Networks (BPN), Self Organized Map (SOM), Multi-Layer Perceptron (MLP), Radial Basis Function (RBF), Adaptive Resonance Theory (ART), Cellular, and Pulse-Coupled neural networks have used for image segmentation. These networks categorized into feed forward and feedback networks. MLP, Self Organized Map (SOM), and RBF neural networks belong to the feed- forward networks [19].

In this paper, we have described about the Self Organized Map. A SOM is a single layer feed forward neural network. SOMs are generally referred as Kohonen's Self Organizing Map. Topological Neural Networks or Self-organizing Feature Maps (SOFM) discovered by Kohonen. SOM used as an alternative of conventional K-means clustering algorithm, but it has more advantages than the K- means clustering algorithm. The main advantage of this method, it has minimum chance to local minima than the conventional K-means clustering algorithm, and acted as a good initialization algorithm for that method. The main advantage is clusters obtained using SOM are topologically ordered. SOM used as a supervised classification by labeling the neurons (or units) with the classes of the data that are mapped to it [20]. Training Algorithm of SOM is given below.

Let

Xt (t = 1 to the number of training patterns N) be the n dimensional training patterns.

Wij be the unit in position (i, j).

$0 \leq \alpha \leq 1$ be the learning rate.

H (Wij, Wmn , r) be the neighborhood function. The neighborhood function has values in the range [0, 1]. It is high for units that are close in the output space and small for units far away. Usually select a function that is 1 if Wij =Wmn, monotonically decreases as the distance in the grid between them increases up to a radius r, neighborhood radius.

The training algorithm consists of the following steps,

For each input, pattern Xt,

1. Calculate the distances between the pattern Xt,and all units Wij

$$Dij = \|Xt - Wij\| \tag{13}$$

2. Select the nearest unit wij as best matching unit Wbmu = Wij

$$Dij = Min(Dmn) \tag{14}$$

3. Update each unit wij according to the rule

$$Wij = Wij + \alpha\, H(Wbmu , Wij , r)\, \|Xt - Wij\| \tag{15}$$

4. Repeat the process until convergence is reached.

IV. Conclusion

In this paper, we have accomplished a partial survey of various techniques for MRI brain image segmentation. The image segmentation based on different algorithms done in a valuable way. The image segmentation techniques may help to enhance the efficiency of the image recovery process. All the techniques may obtain satisfaction results but not able to produce 100 % of accuracy. The image segmentation remains a challenging problem in medical MRI brain image processing, computer vision and still an imminent problem in the world. Further works, we planned to develop a novel efficient technique to produce more accuracy than existing methods for the detection of brain cancer or tumor in MRI images.

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S.Valarmathy is working as Associate Professor in the department of electronics and communication engineering, V.M.K.V.Engineering College, Salem. She has received M.Sc., in Applied Electronics from Cheran arts and science, Bharthiyar University, Coimbatore in 2002 and M.E in Advanced Communication Systems from V.M.K.V.Engineering College, Vinayaka Missions University, Salem 2006. She has 4 international journals published. Her area of research interests includes image processing, embedded system.

R.Ramani is working as Assistant Professor in the Department of Electronics and Communication Engineering, V.M.K.V. Engineering College, Salem. He has received B,E degree in Electronics and Communication Engineering from GCE, Salem, Anna University, Chennai in 2006 and M.E in Communication Systems from Sona college of technology, Salem, Anna University, Chennai in 2008. He has 4 international journals published. His area of research interests includes image processing embedded systems.

Dr. N.Suthanthira Vanitha is working as Professor and head of the department of electrical and electronics engineering at Knowledge Institute of Technology, Salem. She has received Ph.D, in Biomedical & Embedded Systems from Anna University Chennai. 12 years teaching experiences and 14 international journals published in various field. Her area of research interests includes image processing, embedded system. Biomedical and networking.