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Segmentation of Brain MRI Image – A Review

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Abstract— **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.**

Keywords— **Brain, MRI, Segmentation**

I. INTRODUCTION

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 [15]. 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 [15]. 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 [15].

Surgical planning, post-surgical assessment, abnormality detection, and and many other medical application requires medical image segmentation [58]. 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, inhomogenity, 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 [22].

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 [47]. 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 [23]. Apart from this, segmentation of MRI images is essential in clinical diagnosis of neurodegenerative and psychiatric disorders, treatment evaluation, and surgical planning [23].

A. *Imaging modalities*

The primary body constituents are water and bones. Some trace elements such as iodine, iron etc are present in some specific body parts such as thyroid or blood. The principle of medical imaging lies in the efficient use of different properties of those body constituents. The important modalities are x-ray, computed tomography (CT), positron emission tomography (PET), sin- gle-photon emission computed tomography (SPECT), ultrasound and magnetic resonance imaging (MRI). The x-ray, invented by Wilhelm in 1895, is based on the measurement of the transmission of x-ray through the body. But, because of high level of radiation emitted by x – ray may cause diseases such as cancer, skin disease or eye cataract. In x-ray based computer assistance tomography (CT), image is reconstructed from a large number of x-rays. In case of PET, radio nuclides are injected into patient's body which attach to a specific organ. SPECT is a nuclear medicine based tomographic imaging techniques that uses gamma rays and are capable of producing 3D image. The best modality for investigation of soft body tissues is Ultrasound that measures the reflection of ultrasonic waves transmitted through the body.

B. MR imaging (MRI)

Magnetic Resonance Imaging (MRI) is non invasive procedure and can be used safely for brain imaging as often as necessary. MRI images are used to produce accurate and detailed pictures of organs from different angles to diagonise any abnormalities. There are two types of MRI high field for producing high quality images and low field MRI for smallest diagnosis condition. MRI images allow the physician to visualoize even hair line cracks and tears in injuries to ligaments, muscles and other soft tissues. MRI is based on the principle of absorption and emission of energy in radio free range of electron magnetic spectrum. Magnetic resonance imaging (MRI) is excellent for showing abnormalities of the brain such as stroke, hemorrhage, tumor multiple sclerosis or lesions. Accurate anatomical three-dimensional (3D) models derived from 2D MRI medical image data helps in providing precise and accurate diagnostic information about spatial relationships between critical anatomical structures such as eloquent cortical areas, vascular structures etc and other pathological findings which were otherwise indistinguishable by the naked eye(X. Hu et.al 1990).

II. Literature review

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)

A. *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.

1) *A Markov random field method (MRF)*: In this method spatial correlation information is used to preserve fine detail [3], 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.

2) *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 [33]. These make the scaling coefficients independent of the signal and thus can be easily removed [20]. In case of low SNR images, finer details are not preserved [48].

3) *Analytical correction method:* This method attempts to estimate noise and subsequently noise-free signal from observed image. This method uses maximum likelihood estimation (MLE) [43] 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.

4) *Non-local (NL):* This method exploits the redundant information in images [12]. 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.

B. *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. [46]. In the region growing method, thresholding is combined with connectivity. [29].

Fuzzy C – means is a popular method for medical image segmentation but it only considers image intensity thereby producing unsatisfactory results in noisy images. [22]. A bunch of algorithms are proposed to make FCM robust against noise and in homogeneity but it's still not perfect [22] [29] [1] [57] [17] [49].

Accurate estimation of the probability density function (PDF) is essential in probabilistic classification [15]. Nonparametric approach does not make any assumption in obtaining the parameters of PDF thereby making it accurate but expensive [45]. 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 [15].

1) *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 [36] [6] [7] [8] [9] [10] [11].

2) *LVQ:* 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 [47. There are several algorithms to learn LVQ networks.

3) *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 [47]. 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 [47]. Input data is classified according to their grouping in input space and neighboring neuron and moreover learns distribution and topology of input data [47]. 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, [47] 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.

4) *Hybrid SOM:* HSOM 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.

5) *Watershed:* 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 [2] [27]. Its fast implementation method is proposed by [50] and [42]. The over segmentation problem still exists in this method [2] [27].

6) *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.

7) *The 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 internal energy and is used to control the tension and rigidity of the deforming curve. The external energy is used to guide the deforming curve toward the target. [55] used Gaussian Gradient Force to compute external force. Advantages of this method are insensitiveness to contour initialization, boundary concavities, saving computation time, and high accuracy [55].

8) *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 neighbour of pixels [26]. Image segmentation methods use MRF to take advantage of neighbourhood information in the segmentation process, like, in medical images most neighbourhood pixels have the same class and thus by using neighbourhood information, influence of noise in segmentation is decreased.

9) 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 [37].

10) *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. Some methods for brain tumor segmentation can be found in [16] and [24].

11) *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.

III. CONCLUSIONS

Image segmentation is the most challenging and active research area in the field of image processing for the last decade. In spite of the availability of a large variety of state-of art methods for brain MRI segmentation, but still, brain MRI segmentation is a challenging task and there is a need and huge scope for future research to improve the accuracy, precision and speed of segmentation methods. Introducing parallelization and combining different methods can be the future roadmap for making improvement in brain segmentation methods. /because of the ongoing research in biological world, increasing new knowledge about the relationship between different disorders with anatomical deviation is coming up. So, brain segmentation is gaining importance in using as the first stage in tools for detection and analyzing anatomical deviation. For example Alzheimer and Multiple sclerosis (MS) are disorders which can be studied based on deviation in structures of the brain.

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