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Survey on MR Image Segmentation

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Abstract— **an accurate and timely diagnosis of disease is need of medical science as it may increase chances of survival of human being. Segmentation is an essential step in medical imaging analysis and classification. Different image segmentation methods are used for examination of medical images. Efficient segmentation methods lead to accurate diagnosis. However accurate segmentation of MRI (Medical Resonance Image) is very important and crucial for exact diagnosis by computer aided clinical tools.This paper summarizes and compares different methods of brain MR image segmentation**

Index Terms— Brain MR Images, Image Segmentation

I. INTRODUCTION

Brain image segmentation is important process of computer aided clinical diagnostic tools. Because of noise, inhomogeneity and bias field, accurate segmentation of brain images is a very difficult. The process of accurate segmentation of these images is very essential for a correct diagnosis by clinical tools.Segmentation process divides image into several segments. Segmentation simplifies the representation of an image into something that is more meaningful and easier to analyze. Goal of brain image segmentation is to devide a given brain image into non-intersecting regions representing true anatomical structures such as grey matter, white matter etc. Segmented image is get analysed for feature extraction and classification by classifier or pattern recognition sysstem.

There are different techniques to segment an image into subregions such that each region is homogeneous in nature. Because of complexity and inaccuracy not all the methods are suitable for analysis of medical image. There is no standard image segmentation techniques that can produce satisfactory results.Accurate segmentation method is a point of research.MR Image segmentation is a challenging due to its complexity.Segmentation of brain MR images is an important step and has attracted the attention of many researchers for the last decade.This paper is structured into four sections. After this introductory section, the next section gives the major techniques that have been studied as part of the literature survey.Section III summarizes the survey. Finally, we conclude in a section IV.

II. LITERATURE SURVEY

In this section, we are presenting literature survey of image segmentation methods. The key objective is to highlight advantages and limitations of these methods.

Pham and Prince [1] presented an adaptive fuzzy C-means algorithm (AFCM), and added a spatial penalty term into the objective function to allow the estimated membership functions to be spatially smoothed.They proposed an algorithm for fuzzy segmentations of images that has been despoiled by intensity inhomogeneities. Except the initial specification of some parameters, this algorithm is fully automated.

Zhang [2], presented the Hidden Markov Random Field model for Brain MRI segmentation by using expectation-maximization algorithm (EM). This model can easily merge with other techniques. HMRF model is flexible for image modeling as it has the ability to encode both the statistical as well as spatial properties of an image. GHMRF is an extension of a HMRF model with Gaussian that produces images with controllable spatial structure. The EM algorithm is capable method for parameter estimation, and also provides a framework for unsupervised classification.

Ahmed [3] presented algorithm for fuzzy segmentation of magnetic resonance imaging data and estimation of intensity inhomogeneities with fuzzy logic. This algorithm is formed by changing the objective function of the fuzzy c-means algorithm to compensate for inhomogeneities and allows the labeling of a voxel to be influenced by the labels in its immediate neighborhood, which acts as a regularizer. In brief they developed a bias-corrected FCM algorithm by adding a neighborhood averaging term to the objective function. By comparing FCM segmentation algorithm and EM algorithm, the BCFCM performed well on both simulated as well as on real MRI images. However, FCM has advantage that it works for vectors of intensities while bias-corrected FCM algorithm is limited to single-feature inputs.The bias-corrected FCM algorithm technique produced better results than the EM algorithm in noisy images as it compensates for noise.

Greenspan [4] added the spatial constraints into the GMM. Gaussian mixture models represent a well-known type of probabilistic neural networks, in which spatially constrained mixture models has been trained using the expectation maximization algorithm. Numerical experiments on simulated images shows the better performance of method in terms of the maximum value of the objective function and accuracy compared to previous implementations of this approach. A mixture model composed of a large number of Gaussians, and this is used to symbolize the image of brain. Each tissue is represented by a many number of Gaussian components to capture the complex tissue spatial layout. Intensity of a tissue is considered as a global feature and is added into the model by tying of all the associated Gaussian parameters. The expectation-maximization algorithm is used to train the parameter-tied constrained Gaussian mixture model (GMM). Method links the set of Gaussians per tissue type in a way that each Gaussian in the set has correlated intensity characteristics by way of minimum overlapping spatial supports. Segmentation is done by the connection of each voxel to the component of the model that maximizes the posteriori probability.

Yang and Tsai [5] developed an adaptive Gaussian-kernel-based fuzzy c-means algorithm (GKFCM) with the spatial bias correction. Bias-corrected fuzzy c-means algorithm with spatial information is very efficient in segmentation of images.Some of the kernel versions of FCM with spatial constraints such as KFCM_S1 and KFCM_S2, were proposed to solve drawbacks of bias corrected fuzzy c-means algorithm, where KFCM_S1 and KFCM_S2 are closely affected by their parameters. In short Yang and Tsai presented a Gaussian kernel-based fuzzy c-means algorithm with a spatial bias correction. The Gaussian-kernel-based fuzzy c-means algorithm becomes a generalized algorithm of FCM, BCFCM, KFCM_S1 and KFCM_S2 and provides more robustness and efficiency.

Liao [6] developed a spatially constrained fast kernel FCM (SFKFCM) clustering algorithm to progress the computational efficiency. The clustering performed in a kernel space is a very time taking process. A fast spatially constrained kernel clustering algorithm is presented for brain MRI image segmentation, and correcting intensity inhomogeneities known as bias field in MRI data. The kernel technique implicitly maps image data to a higher dimensional kernel space to enhance the separability of data and provide more potential for effectively segmention of MRI data. Bias field correcting and fast kernel clustering help each other in an iterative manner and have dramatically reduced the time complexity of kernel clustering.

Zeng [7] proposed the type-2 Fuzzy Guassian mixture model (T2-FGMM) for density modeling and classification. Fuzzy extensions of the GMM based segmentation algorithm have not been able to defeat the difficulties generated due to intensity inhomogeneity.

Li [8] presented an energy minimization method for simultaneous tissue classification as well as bias field estimation of magnetic resonance images. Researcher derived a main characteristic of local image intensities.Then intensities of different tissues in a neighborhood forms separable clusters, and cluster center can be approximated by the product of the bias within the neighborhood and a tissue-dependent constant then introduced a coherent local intensity clustering criterion function as a metric to evaluate tissue classification and estimation of bias field. An integration of this metric defines energy membership functions of the tissues on a bias field and the parameters that approximate the true signal from the corresponding tissues. Bias field estimation and tissue classification are simultaneously achieved by minimizing this energy. The spatially coherent nature of the CLIC criterion function is use to ensure smoothness of the derived bias field. Extra effort is not required to smooth the bias field in proposed method.

Xia [9] added the global information into the coherent local intensity clustering model to improve its robustness, then Xia presented a newly modified possibilistic fuzzy c-means clustering algorithm (MPFCM) for bias field estimation and segmentation. A modified possibilistic fuzzy c-means clustering algorithm is proposed for fuzzy segmentation of MR images that have been spoiled by intensity inhomogeneities and noise. Xia proposed an adaptive method to compute the weights for the neighborhood of each pixel in the image. The proposed adaptive method not only defeats the effect of the noise efficiently, also prevents the edge from blurring. MPFCM introduces the global intensity into the CLIC algorithm to deal with intensity inhomogeneity and combines the global and local intensity information into account to make sure the smoothness of the derived optimal bias field as well as improves the accuracy. MPFCM model can be treated as a general framework of FCM, PCM, CLIC and PFCM.With good initialization; the MPFCM model may need less iteration and can obtain results in fewer times. A variety of synthetic brain MR images and real brain MR images are used to compare the performance of the MPFCM algorithm. Results show that the proposed method is efficient, more robust and more accurate for both 3D and 2D brain MR image segmentation.

Xia [10] pesented Fuzzy Local Gaussian Mixture Model for Brain MR Image Segmentation.This approach proposed the fuzzy local Gaussian mixture model (FLGMM) algorithm for automated brain MR image segmentation by assuming local image data contained by each voxel’s neighborhood satisfy the Gaussian mixture model GMM for accurate brain image segmentation. FLGMM maximizes the posterior probability by means of minimizing an objective energy function, in that a truncated Gaussian kernel function is used to enforce the spatial constraints and fuzzy memberships are used to balance the contribution of each GMM. This algorithm improves the accuracy of brain MR image segmentation.

III. Comparative Study Of Different Segmentation Techniques

A review of the studied literature is summarized in the compare table (TableI) with advantages and disadvantages of different segmentation techniques. Most of the key features of methods are mentioned in table with respective limitations that makes our work unique.

TABLE I. COMPARE TABLE

Author	Summary	Proposed Technique	Algorithm Used	Benefits	Identified Problems
Pham (1999)	Adaptive Segmentation of MR images	Segmentation of MR images	Adaptive Fuzzy c-means	Useful for gain field estimation and inhomogeneity corrected images.	It tends to look for clusters of same shape and size.It can be sensitive to excessive noise.
Zhang (2001)	Segmentation of brain MR images	Brain MR image segmentation	Expectation Maximization	Technique possesses ability to encode both spatial and statistical properties of an image.	The method requires estimating threshold and does not produce accurate results most of the time.
Ahmed (2002)	MRI data segmentation	Bias field estimation and segmentation	Modified fuzzy C-means	BCFCM algorithm is faster to converge to generate accurate classification. Useful in scan corrupted by salt and paper noise	Technique is limited to a single feature input.
Yang and Tsai (2008)	MRI data Segmentation	Segmentation of MR Images	A Gaussian kernel-based fuzzy c-means algorithm with spatial bias orrection	Generalized type of algorithms and presents with more robustness	Computational efficiency need more improvement
Liao (2008)	Bias field correction and MRI brain image segmentation	SKF-FCM is proposed for brain MRI image segmentation, and correcting intensity inhomogeneities known as bias field in MRI data.	Spatially constrained fast kernel FCM(SKF-FCM)	It provides more potential for effectively segmenting MRI data.	Accuracy can be improved.
Greensp an (2006)	A study of Gaussian mixture models of texture and color features for image classification and segmentation	Brain MR images can be segmented by using the Gaussian mixture model (GMM), where the voxel intensities in each target region are modeled by a Gaussian distribution.	Gaussian mixture models (GMMs) and EM framework.	An automated algorithm for tissue segmentation of low-contrast, noisy magnetic resonance (MR) images of the brain	Lack of taking the spatial information and uncertainty of data into consideration, Less accuracy.
Zeng (2008)	Type-2 fuzzy Gaussian mixture model.	Gaussian mixture models (GMMs)	Presents a new extension of Gaussian mixture models based on type-2 fuzzy sets	It gives model for density modeling and classification	Unable to overcome the difficulties caused by the intensity
Li (2009)	MRI tissue classification and bias field estimation based on coherent local intensity clustering:A unified energy minimization framework(CLIC)	Li introduced a coherent local intensity clustering (CLIC) criterion function as a metric to evaluate tissue classification and bias field estimation based on an important characteristic of local intensities in MR images.	CLIC model	Able to estimate bias field in high and ultra high field MR images	The membership function cannot be estimated accurately because not all the pixels in the kernel belong to the same tissue, which cause misclassifications
Xia (2011)	Bias field estimation and segmentation of brain MR images	To address intensity inhomogeneity, algorithm introduces the global intensity into the CLIC algorithm and combines the local and global intensity	A modified possibilistic fuzzyc-means clustering algorithm	Adaptive method can not only defeat the effect of the noise effectively, but also prevent the edge from blurring.	Time consuming
Xia (2012)	Segmentation of brain MR Images	Fuzzy Local Gaussian mixute model for brain mr image sementation	FLGMM	This algorithm can largely overcome the difficulties raised by low contrast, noise and bias field	This algorithm is a bit time consuming when applying to large 3D images.

IV. Conclusion

Image segmentation is the most challenging research area in the field of image processing. In spite of the availability of large number of methods for brain MRI segmentation, still brain MRI segmentation is a challenging task as the accuracy is concerned. A survey of several segmentation approaches has been done. In this study, the various segmentation techniques are explained briefly with key objectives and limitations. This literature study provides a simple guide to the researchers.

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