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A Review:FPGA Based Image Segmentation for Medical Images

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ABSTRACT: Image segmentation plays very important role in various medical imaging application. Tumor segmentation is a difficult task due to the large difference in the presence of tumorous tissues. The collection of abnormal cells that nourish in the brain is known as tumor. In this paper a new level set based deformable model is proposed for segmentation the medical images. The segmentation of image can be done efficiently even when there are weak edges and gaps. Regional data analysis and the gradient information is used to deform the level set. This method can automatically handle the changes in the image and permit number of simultaneous boundary estimation. In this proposed method image segmentation is done using Spartan-III FPGA .

KEYWORDS: Medical images, Level set , Image processing, FPGA.

I.INTRODUCTION

MRI(Magnetic resonance imaging) is a high tech imaging technique that allows the powerful magnetic field, radio pulses and a computer to produce detailed pictures of organs, tissues, bones and cross sectional vision of the body with paralleled tissue disparity. MRI displays the brain condition associated to usual and unusual brain structures and function. MRI gives detailed information about the structure of brain and nerve tissues in multiple planes without obstruction by overlying bones.

Brain tumor is a set of abnormal cells that appear inside the brain or around the brain. Brain tumor can directly remove all the healthy brain cells. It also damage the healthy tissues or strong cells by intersecting further parts of the brain. The brain tumor leads in inflammation, brain swelling and pressure within the skull. The tumor differ in size ,range of shape and location properties that overlap with regular brain tissues. The spreading tumor can detect and distort the nearest cells in the brain providing an abnormal geometry to the healthy tissues.

Image segmentation plays an crucial role in the medical imaging applications such as recounting the tissues volumes diagnosis, confinement of pathology analysis of anatomical structure, treatment planning, partial volume improvement. The objective of image segment is to identify structures in the image . The task of image segmentation is to divide an image into two non-overlapping regions that depends upon intensity or textural information or they are homogeneous with respect to some characteristic.
Geometrical deformable model or level set based deformable or active contours have various applications in many fields of medical image segmentation . The rest of the paper is organized as follow, the section II describes literature survey in short. Section III illustrates the different tumor segmentation techniques. Section IV describes the proposed method.

II.LITERATURE SURVEY

A plentiful of work has been proposed by researches for MRI segmenting and for tumor detection techniques. A brief review of some methods is presented here. The segmentation methods are,

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2. •Region growing Approach
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4. •Clustering Approach
5. •Markov Random field model
6. •Atlas guided approach
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1. Thresholding Approach

In the thresholding method the scalar images are segmented by conferring a binary partitioning of the intensities in the image. The desired classes are separated depending the particular intensity value and that intensity value is known as the threshold value. After obtaining the threshold value the segmentation is done by grouping all pixels with intensity greater than the threshold into one class and other pixels into other class . If more than one value of threshold is determine than this process is known as multi-thresholding.

Thresholding is a simple while obtaining segmentation in images with different structure and with different intensities or other contifiable features. The partition of image is generated interactively even though there are automated methods for the scalar images, the interactive methods are depend upon the operators visual assessment of the segmentation as the thresholding operation can be implemented in the real time.

In the image processing operations the thersholding is used as an initial step. The disadvantage of this method is that it cannot be applied to the multichannel images as it is a simple form and it only form two classes. The spatial characteristics of an image are not considered in the thresholding. Due to this they are sensitive to noise and intensity inhomogeneities that usually occur in magnetic resonance images. for medical images the classical thersholding depends on the information of local intensities and connectivity.

2. Region growing approach

Region growing is a simple method which is based on region for segmenting an image. It is a technique that uses the information of region in an image that is connected to some predefined criteria. The predefined criteria is based on the intensity values and edges in the image. The region growing requires a seed point .The seed point should be selected manually. The region growing starts from this seed point, the pixels which satisfies the intensity constraints that are extracted. Region growing is used within a set of image processing operation for the small and simple structures such as tumors and lesions. The disadvantage of region growing is that the seed point should be selected manually. Region growing is sensitive to noise which may cause the holes or gaps in the extracted regions.

3. Classifiers

Classifier methods are based on the pattern recognition techniques. This technique seeks to the partition a feature space obtained from the image. A feature space is nothing but the range space of any function of the image. Classifiers are also called as supervised methods. They require training data that are manually segmented and afterwards they are used as references for automatically segmenting new data. There are a number of ways in which training data can be applied in classifier methods. A simple classifier is the nearest-neighbour classifier, where each pixel or voxel is classified in the same class with the closest intensity. The kNN classifier is considered a nonparametric classifier since it makes no underlying assumption about the statistical structure of the data. The next nonparametric classifier is known as the Parzen window, in which the classification is done based on the majority vote in a predefined window of the feature space centered at the unlabeled pixel intensity. The most commonly-used parametric classifier is known as the maximum likelihood (ML) or Bayes classifier. It considers that the pixel intensities are independent samples from a

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mixture of probability distributions, mostly Gaussian. Standard classifiers require the structures to be segmented with distinct quantifiable features. Because training data can be labeled, classifiers can give these labels to new data as long as the feature space sufficiently distinguishes each label as well. Being non-iterative, they are relatively computationally efficient and unlike thresholding methods, they can be applied to multi-channel images. A disadvantage of classifiers is that they do not perform the spatial modeling. This disadvantage has been addressed in recent work extending classifier methods to segmenting images that are corrupted by intensity inhomogeneities. The one more disadvantage is the requirement of manual interaction for obtaining training data. Training sets can be obtained for each image that requires segmenting, but this can be time consuming and laborious.

4.Clustering

Clustering algorithms perform the similar function as classifier methods except they do not use the training data. Thus, they are known as unsupervised methods. Clustering methods iterate between segmenting the image and characterizing the properties of the each class. Clustering methods train themselves using the available data. Three commonly used clustering algorithms are the K-means or ISODATA algorithm, the fuzzy c-means algorithm and the expectation-maximization (EM) algorithm . The K-means clustering algorithm clusters data by iteratively computing a mean intensity for each class and segmenting the image by classifying each pixel in the class with the closest mean. The fuzzy c-means algorithm generalizes the K-means algorithm, allowing for soft segmentations based on fuzzy set theory . The EM algorithm applies the same clustering principles with the underlying assumption that the data follows a Gaussian mixture model. It iterates between computing the posterior probabilities and computing maximum likelihood estimates of the means, covariances, and mixing coefficients of the mixture model. Although clustering algorithms do not require training data, they do require an initial segmentation (or equivalently, initial parameters). The EM algorithm has demonstrated greater sensitivity to initialization than the K-means or fuzzy c-means algorithms. Like classifier methods, clustering algorithms do not directly incorporate spatial modeling and can therefore be sensitive to noise and intensity inhomogeneities. This lack of spatial modeling, however, can provide significant advantages for fast computation . Work on improving the robustness of clustering algorithms to intensity inhomogeneities in MR images has demonstrated excellent success. Robustness to noise can be incorporated using Markov random field modeling as described in the next section

5.Markov random field models

Markov random field (MRF) modeling itself is not a segmentation method but a statistical model which can be used within segmentation methods. MRFs model spatial interactions between neighboring or nearby pixels. These local correlations provide a mechanism for modeling a variety of image properties . In medical imaging, they are typically used to take into account the fact that most pixels belong to the same class as their neighboring pixels. In physical terms, this implies that any anatomical structure that consists of only one pixel has a very low probability of occurring under a MRF assumption. MRFs are often incorporated into clustering segmentation algorithms such as the K means algorithm under a Bayesian prior model . The segmentation is then obtained by maximizing the *a posteriori* probability of the segmentation given the image data using iterative methods such as iterated conditional modes or simulated. A difficulty associated with MRF models is proper selection of the parameters controlling the strength of spatial interactions . Too high a setting can result in an excessively smooth segmentation and a loss of important structural details. In addition, MRF methods usually require computationally intensive algorithms. Despite these disadvantages, MRFs are widely used not only to model segmentation classes, but also to model intensity inhomogeneities that can occur in MR images and texture properties.

6.Atlas-guided approaches

Atlas-guided approaches are a powerful tool for medical image segmentation when a standard atlas or template is available. The atlas is generated by compiling information on the anatomy that requires segmenting. This atlas is then used as a reference frame for segmenting new images. Conceptually, atlas-guided approaches are similar to classifiers except they are implemented in the spatial domain of the image rather than in a feature space. The standard atlas-guided approach treats segmentation as a registration problem for a detailed survey on registration techniques). It first finds a one-to-one transformation that maps a pre-segmented atlas image to the target image that requires segmenting. This process is often referred to as atlas warping. The warping can be performed using linear] transformaions but because of anatomical variability, a sequential application of linear and non-linear transformations is often used. Atlas-guided

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approaches have been applied mainly in MR brain imaging. An advantage of atlas-guided approaches is that labels are transferred as well as the segmentation.

III. PROPOSED TRANSFORM

In this proposed method the segmentation of an image is done by using a new level set deformable model. The level set based approach for segmenting an image uses the gradient information as well as regional data analysis. This method can automatically handles the changes in the images. The segmentation method uses both edge and region based information. For detection of tumor the threshold values are considered that are based on the intensity value .The method is well suited for detecting the tumor as it segment the image even when there are weak edges and gapes. A level set deformable model can work over high resolution medical data as well as low resolution medical data.

IV. CONCLUSION

A new level set based method for tumour segmentation is introduced which will not miss even the blurred boundaries. The deforming contours handle the topological changes naturally and expand or shrink as necessary, and automatically identify the tumour voxels. Regional statistical measures are integrated into the gradient so that the deforming contour with high precision is obtained.

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