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REVIEW ARTICLE

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Review of Recent Advances in Segmentation of Lesion in the Breast DCE-MR images

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Abstract: Breast tumor detection and segmentation in dynamic contrast enhanced magnetic resonance images (DCE-MRI) is important in medical diagnosis because it provides information related to the lesion or abnormal tissues necessary for diagnosis of the disease and treatment planning. The segmentation of breast tumors can also be helpful for general modelling of pathological breasts and the construction of pathological breast atlases. Despite numerous efforts and promising results in the medical imaging community, accurate segmentation for description of abnormalities are still a difficult and challenging task because of the diversity of shapes and image intensities of various types of tumors. Some of them may also deform the surrounding structures or may be associated to edema or necrosis that changes the image intensity around the tumor. Existing methods provides significant scope for increased automation, robustness, sensitivity and accuracy. In general there is a necessity to design robust and fast segmentation algorithms. However, there is no generic method for solving all segmentation problems. Instead, the segmentation algorithms developed are highly adapted to the application in order to achieve better performance. In this paper, the review of recent developments in segmentation methods for lesion detection in breast DCE-MR Images is presented.

Keywords: Breast DCE-MR images, Segmentation methods.

I. INTRODUCTION

Breast cancer continues to be a major public health problem in the world. The grounds for breast cancer are still unidentified and are not prevented in any certain approach. Early identification of the disease represents a very essential factor in its treatment planning and consequently increasing the survival rate. Recent studies have revealed that cure rates considerably increase, if the breast tumor can be detected.

The role of segmentation in case of medical image segmentation is to study anatomical structure, identify region of interest i.e. locate tumor, lesion and other abnormalities, measure tissue volume to measure growth of the tumor, help in treatment planning prior to radiation therapy; in radiation dose calculation. The segmentation of medical images is more significant, when the physician decides the type of recovery process based on the image segmentation results [1].

Image segmentation is the process of separating objects from background; it is the process of representing information in an image in to group of pixels together into regions of similarity [1]. The basic assumption is that the object in the image differs from the background (i.e., everything that is not part of the object) in some properties (e.g. shape, intensity, texture). The result of a segmentation method is usually a list of equivalence classes where each class represents an object or the background.

Image segmentation can be categorized to boundary and regional representations. Each type of representation is the identification of homogeneous regions or shape of local inhomogeneity, respectively. The monochrome image segmentation algorithms are generally based on discontinuity and similarity properties of gray-level values.

Classification of objects (e.g. lesions) in the spatial domain is commonly based on the segmentation and different properties of the image, such as morphometric (i.e., shape, size), radiometric (i.e., gray level, histogram) and textural properties. The first step in object classification is usually the segmentation of the object of interest in the image. Robust segmentation is difficult to achieve; thus, the classification process is often expected to overcome the noise and bias that may be introduced by the segmentation step.

Manual segmentation is subjective and given the huge quantity of data to be analyzed in a DCE-MRI data set, the possibility exists that diagnostically-significant regions of enhancement may be overlooked. However, automatic segmentation is challenging, because the temporal and spatial distributions of the contrast agent in suspicious lesion tissue can be highly varied.

II. EXPLORATION OF SEGMENTATION METHODS FOR GRAY SCALE IMAGES

The segmentation of an image is the partitioning of an image into a set of connected regions, where each region is homogeneous in some sense (e.g. intensity or texture) and is identified by a unique label. When the constraint that the regions are connected is removed, then segmentation is called pixel classification and the partitions are called classes. Segmentation methods can generally be categorized into discontinuity-based and similarity-based approaches [2].

Discontinuity-based methods concentrate on the sharp local changes in image intensity. Methods incorporate edge detection followed by edge linking and the watershed algorithm, which uses edge detection and mathematical morphology methods to partition the image into set of homogeneous regions. Discontinuity-based approaches suffer from false and missing edges since intensity gradients are more affected by noise than the image intensity. Deformable models, like snakes, balloons and level-sets, have been developed to overcome this problem. They are based on deforming a closed boundary under the influence of shape-based forces and image derived forces [3]. The shape-based force can incorporate a priori knowledge about the location, size and shape of the structure. Various shape models have been proposed ranging from general smoothness cost functions to application specific statistical shape templates learned from a training set.

Similarity-based methods are based on the homogeneity characteristics of a set of pixels. Using the global intensity statistics, pixel can be unsupervised classified into set of regions, by using one of the following methods: simple thresholding, K-means clustering or the EM algorithm [4]. Difficulties occur from noise, image inhomogeneities, selecting number of clusters and sensitivity of the cluster algorithms to the initialization procedure used and incorrect assumptions regarding the data distribution. Improvements can be achieved by incorporating prior knowledge from manually segmented images. Artificial neural network (ANN) approach is a better choice for image segmentation. The properties of ANN, like dreadful condition in the occurrence of noise, capability of providing efficient segmentation even in real-time application. ANN has become an effective method for segmentation. Almost all the types of neural networks have been used for segmentation. Mostly kohonen and hopfield ANNs are used for segmentation. Kohonen self-organizing maps (SOMs) for image clustering is discussed in [1, 5, 6], a survey of Hopfield neural networks (HNN) in image segmentation is demonstrated in [7, 8]. Segmentation techniques review has been presented in [9] and predicted that artificial neural networks would become broadly applied in image processing applications. Segmentation, based on artificial neural networks is found to confirm rich potential [10]. An alternative related work in the field of medical image processing confirms neural network for image segmentation. The approach was conjugated with real time applications. A hybrid neural network was proposed in [11]. In the past few years many segmentation techniques have been developed but there is no standard segmentation technique that can produce a reasonable outcome for all types of imaging applications. Still, the neural network based approach has proven to be more efficient than other techniques. Pixel classifiers do commonly not perform any spatial modeling and hence are very sensitive to noise. Markov random field models, which are statistical models that define the relationship between nearby pixels, are therefore often incorporated to improve the robustness to noise. Though pixel classification relies on the global intensity statistics, similarity-based segmentation can be based on the statistics from the individual regions. In region growing, for example, a region may be expanded by neighbouring pixels if their intensity values lie within a certain standard deviation of the mean intensity value of the region. Drawbacks of region growing are wrongly connected regions due to noisy boundaries and partial-volume effects. Region competition [12], which combines deformable contours and region growing, has been proposed to overcome these problems. Both methods require good initial regions.

In particular, segmentations and pixel classifications simply based on image features, which generally fail due to noise, inhomogeneities and partial volume effects. Incorporation of prior knowledge in the form of shape, class or neighborhood models has been successful for certain applications. In the case of segmenting DCE-MR images, shape and general class models are unlikely to be suitable due to the high variability of the lesions shape, size, location and image properties. Case specific class models, as derived for example from coarse manual segmentations, are a promising semi-automatic framework for more accurate segmentations. Similarity-based methods can relatively easily be extended to multichannel images.

III. REVIEW OF RECENT BREAST LESION SEGMENTATION TECHNIQUES FOR DCE-MR IMAGES

Breast medical images can be acquired in several ways. Among which are the ultrasound, X-ray mammograms, computed tomography (CT), nuclear medicine and MRI (including DCE-MRI). Each modality yields a slightly different image that presents different properties of the same object. However, all acquisition results are translated to a discrete image that represents the local average intensity of the observed property of the tissue in each pixel/voxel in the image.

In an ideally segmented image, each region should be homogeneous with respect to certain predicate, such as gray level or texture and adjacent regions should have significantly different characteristics or features. Segmentation is a fundamental tool which aids in identification and quantitative evaluation. The goal of medical image segmentation is to assign a unique label to each voxel in the gray–level input image; each unique label represents an anatomical structure. It conditions the quality of analysis.

When trying to detect malignant tissue in a breast volume, it is assumed that malignant tissues have different characteristics of benign tissue, in the scale of the acquisition intensity results. The differentiation can appear either in rough intensity, in boundary shape, texture or any combination of them. In dynamic imaging, differences can also be observed on the time axis.

One of the common segmentation methods is the seeded region growing (SRG). Variations of this method are often used in the transformation of the information extracted from the image, such as the density weighted contrast enhancement (DWCE) [13]. Moreover, SRG-based methods in the literature often rely on manual seed selection, which requires the user to review the data and identify the regions of interest.

A semi-automated software algorithm for segmenting breast tumors from 3D MRI data using thresholding was developed by [14]. A threshold based on the tumor enhancement ratio was applied on a voxel-by-voxel basis within the manually defined volume in their study. A three threshold based segmentation approach in [15] also used thresholding to segment the enhancing region from the difference image (computed by subtracting the pre-contrast image from the post-contrast image). They estimated three different threshold selections: A constant threshold, a threshold derived from a histogram and a threshold defined as some percentage of the maximum value in the image data. The voxel intensity of an MR image depends on the type MRI machine and contrast agent used, thus selection of the threshold values must be carefully done by the user. In addition, the same tissues may not be enhanced uniformly by the contrast agent and this also decreases the accuracy of threshold-based methods.

Fuzzy c-means (FCM) clustering-based method proposed by [16, 17] for 3D lesion segmentation in dynamic contrast-enhanced MRI (DCE-MRI) data. The FCM algorithm is applied as an unsupervised learning technique to the enhancement kinetic curves of each voxel from five time points and the ROI voxels are partitioned into two categories: Suspicious lesion and non-lesion. Segmentation method discussed in [18] analyzes the kinetic curves of voxels in dynamic MRI data and classified them as lesion or non-lesion regions based on the Bayesian theory and Markov random field model. A new method for segmenting malignant lesions from DCE-MR images based on four-dimensional co-occurrence-based texture analysis is presented in [19]. The textural features, gathered from statistical information regarding the change in voxel intensities over time, were used as the input of a model-free neural network-based classifier in their study. In these methods, complete series of dynamic data are required to obtain the voxel intensity changes over the entire DCE-MRI. If used in a pre-processing step, the registration of the serial images may improve the performance of the algorithms by lessening the effects of motion and breathing during acquisition of the serial MRI data [16, 18].

Without using serial MRI data, method proposed in [20] uses a dynamic-programming-based optimal edge detection method to segment the breast suspicious lesion from one volume of dynamic contrast-enhanced MRI data. Segmentation algorithm specified in [21] also performed their algorithm on a single volume of post-contrast, T1-weighted data to segment breast tumors. Their method was based on 3D level set segmentation within a manually defined region of interest. Both dynamic programming and level set methods achieve better segmentation results in isolated tumors with relatively smooth margins, but for scattered small foci of tumor (often seen in treating breast cancer) or speculated tumors, these methods may be of limited value.

The segmentation method introduced in [22] reduced the image sequence to a single image by voxel wise computing the variance of the intensity values over time for all voxels within the breast. Self-organizing Kohonen maps is employed in [23] for clustering the intensity enhancement profiles. A combined segmentation and registration approach proposed was in [24], in that breast tissue was firstly segmented into fatty and non-fatty tissue based on a K-means clustering of the pre-contrast image. For a given transformation, the non-fatty tissue was then segmented into normal, benign and malignant tissue based on two kinetic features.

Gradient vector flow (GVF) snake based segmentation method proposed in [25]. The results obtained in the GVF segmentation method in this detailed study were satisfactory referred to the radiologist's manual segmentation or ground truth. The GVF snake segmentation method can possibly provide with an accurate segmentation in breast lesion borders.

The segmentation method proposed by [26] consists of generating a library of texture primitives called "textons" and then clustering each voxel into different tissue classes using textons and vector attributes. A markov random measure field (MRF) method is combined with texture information to realize the spatial coherence.

A novel fully automated system developed by [27] is introduced to facilitate lesion detection in dynamic contrast-enhanced, magnetic resonance images (DCE-MRI). A cellular neural network is used in the system to extract the breast regions from pre contrast images, then generates normalized maximum intensity-time ratio (nMITR) maps and performs 3D template matching with three layers artificial neural network of 12x12 cells to detect lesions.

In the method proposed by [28], the breast DCE- MR images were converted into binary images. The undesired noise and artifacts are removed by applying multiple morphological operations. A chest contour mask was generated to separate the breast regions from the chest. The chest contour mask was applied to each frame to eliminate the chest region. This method was compared against manual segmentation and different performance indexes were evaluated.

A new fully automatic method of suspicious lesion extraction from breast DCE-MR images was developed by [1], the image is pre-processed and converted into feature vector for easier analysis [29]. The enhanced SOM based K-means algorithm is used for segmenting the lesion in the given breast DCE-MR image; this method utilizes edge enhancement technique proposed in [30] for efficient detection of lesion, followed by proper thresholding the lesion is efficiently extracted. This method was evaluated and it produces better results compared with existing different clustering techniques for segmentation such as SOM (Self Organising Maps), k-means and fuzy C-means [31].

An intelligent segmentation algorithm based on swarm bee algorithm in extracting mass lesion from breast DCE-MR images has been proposed by [32]. The method employs the artificial swarm bee colony algorithm to search for the set of K cluster centers that minimizes a given clustering metric. The bee's algorithm converged to the maximum or minimum without becoming trapped in local optima. The algorithm generally outperformed other techniques that were compared with it in terms of speed of optimisation and accuracy of the results obtained.

The segmentation algorithms proposed in [1] and [32] are compared with the same breast DCE-MR image dataset and according to comparisons, the ABC algorithm has provided refined accurate segmentation image with detail abnormal tissue [33].

Among many MRI segmentation methods, artificial intelligence techniques attracted more and more researchers for using it for breast DCE-MRI segmentation. Image segmentation is an important requirement of many artificial intelligence systems. Though great effort has been devoted to inventing efficient algorithms for image segmentation, there is still much work to be done. A fully-automatic segmentation algorithm with a high sensitivity to suspicious lesions is thus desirable.

IV. EVALUATION OF SEGMENTATION METHODS

Segmentation in DCE-MRI images has substantial diagnostic power, such that it has potential to assist physicians in the assessment of volume changes. The enhancement of the lesions on the images makes DCE-MRI a valuable technique for better segmentation of breast lesions. There are many performance measures to test the segmentation algorithm but sensitivity is the most common performance measure, which tests the ability of the segmentation algorithm, the ability to produce results that are consistent with ground truth. Robustness of the algorithm is an important criterion for the laboratories to adapt a new MRI segmentation technique. Due to the increase in different device specifications in MR Imaging, new segmentation algorithms and detection methods have been continuously evolved and introduced. It is a difficult task to select the most appropriate segmentation algorithm or method for a particular application. In such circumstances a combination of more than one segmentation techniques may be combined together to obtain the desired segmentation algorithm. Therefore, in current scenario hybrid or combination of segmentation methods can be used in breast DCE –MR Image segmentation applications. By combining different complementary methods to form a hybrid method, it is possible to evade most of the drawbacks of each method and improve the overall performance, which will improve the robustness, computation time, sensitivity and overall segmentation accuracy.

V. CONCLUSION

The aim of this review is to give an overview of the different methods that exist for breast lesion segmentation in DCE-MRI. In this collection of methods, semi-automatic and full automatic methods were discussed. In spite of the availability of a large variety of state-of art methods for breast DCE-MRI segmentation, but still, breast DCE- MRI segmentation is a challenging task. A segmentation method may perform well for one breast DCE-MR image but not for the other images of same type. Thus it is very hard to achieve a generic segmentation method that can be commonly used for all breast DCE-MR Images and there is a need and huge scope for future research to improve the accuracy, precision and computation speed of segmentation methods. Introducing parallelization and combining different methods to develop several novel hybrid approaches makes the future path for building improvement in breast DCE-MR image segmentation methods.

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