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Segmentation in Medical Image Processing - A Survey

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Abstract— The main task of this work is to survey the various medical image segmentation methods analysed by researchers. Segmentation plays a crucial role in medical image processing. It is often used to pinpoint the objects and retrieve pertinent information in an image. Image is acquired with collection of objects having different intensities. The process of image segmentation is assessed through the different intensity level of the objects. Segmentation basically starts from threshold, histogram, clustering, edge based and many other methods. This paper analyses various medical image segmentation methods with their applications. Also it discusses with recent developments in segmentation techniques that are proposed for multiple diagnostic issues.

Keywords— Clustering, Histogram, Medical Image Segmentation, Thresholding, Region Based.

I. INTRODUCTION

Medical image segmentation plays a pivotal role in many medical image applications. This paper reviews some existing medical image segmentation algorithms including general segmentation. Medical imaging benefits the patients through more precise and rapid disease management, fewer side effects, ameliorated diagnosis, and more cost-efficacious treatment. Since manual segmentation is a tedious and time-consuming procedure, automated segmentation is much desired in many applications. Medical image segmentation is one in all the foremost necessary and tedious tasks in several medical image applications. Segmentation aims at partitioning a medical image into its constituent regions or objects and isolating multiple anatomical parts of interest within the image. The entire success of an application may depend upon the accuracy of segmentation. Therefore, considerable care should be taken to improve the reliability and accuracy of segmentation in medical image analysing and processing.

The difficulties of medical image segmentation are

a) Pixel intensity is usually not homogeneous. Intensity inhomogeneity can fail several segmentation strategies based on intensity homogeneity.
b) Many medical images are still noisy and have low contrast.
c) Dealing with noise and low contrast without losing accuracy is a very challenging task for medical image segmentation.
d) Medical images have many variable properties. The variability of anatomical parts makes the representation of prior knowledge very hard.

Segmentation of the overlapping anatomical parts is very difficult because of the complication of the overlapping regions [1].

Segmentation is used in major field of science which cannot be neglected. Segmentation techniques have been broadly classified into three types which are based on i) Classical method, ii) hybrid techniques and iii) AI Techniques. Medical image segmentation has many techniques and procedures which are followed including atlas based, cluster based, thresholding, watershed, region growing methods and so on.

The process of dividing images into homogenous regions is done by image segmentation which is categorizes as soft and hard image segmentation. In the feature space, for each point, a confidence value is computed in the soft image segmentation. Several research groups have proposed and developed techniques to segment the regions in various image modalities such as CT, X-rays, MRI, PET, Ultrasound etc., Segmentation plays an important role in various pathologies detection which are brain tumour, human thyroid, cardiac wall segment, Lung cancer position in lung image segments, pulmonary nodule detection, lung airway segment, lung lobe segmentation, border detection in coronary angiograms, planning of surgery, detection of blood cells automated classification, mass detection in mammograms, segmentation of heart and analysis of cardiac images etc.

Image segmentation techniques can be broadly classified as Pixel based, Region based, Edge based, Fuzzy Models, Neural Network based and Deformable Models based techniques.

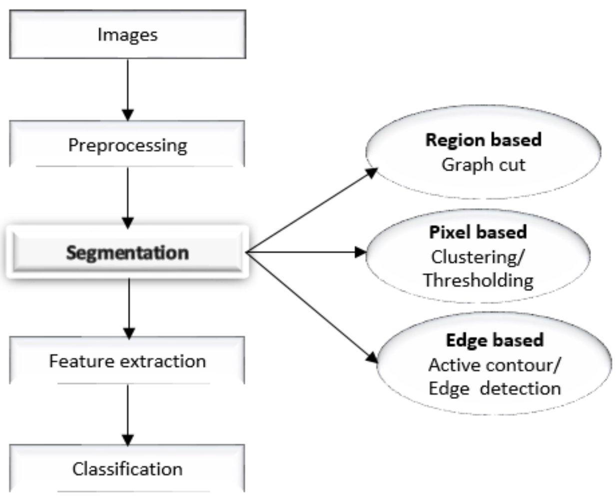

Figure 1. Various Segmentation methods

Pixel based: In this method gray level values are considered for segmentation of each pixel which have a threshold value for segmentation. Defining the threshold has different techniques and methods which can be categorized as Global and local thresholding. Local thresholding is also known as adaptive thresholding.

Region based: In this technique, homogeneous regions are formed by grouping the gray levels from the neighbour pixel into regions. For instance, it is used to extract the lesion from the background image during the process of segmentation of mammogram images.

Edge based: Discontinuity calculations are used in this method to determine the edges of the image segments. Edge detection and linking are the two basic methodologies for segmentation. Prewitt operator, Sobel operator and Laplacian of Gaussian operator are some of the standard operators for the process of edge detection.

Fuzzy Models: In this method of segmentation, a membership level is linked with the data elements which can belong to a number of clusters. This membership level is used by the fuzzy methods to allocate the above said data elements to the clusters.

Neural Network based: Pixel-Label mapping is done in this technique. Small regions of an image are processed by the use of artificial neural network in the process of neural network segmentation. Further, the image areas are identified into different categories, which are done by the concurrence of the decision making system.

Deformable Models: One of the wide applications in the field of medical image segmentation. Here, the best delineation is identified to mark the probable boundary of an object. For instance, a rubber band is a typical example where it has a deformable nature, trying to stay as close to the object contours. X-ray, MRI and CT scan images have been used to apply the test models [18].

Rest of the paper is organized as follows, Section I contains the introduction and the various segmentation methods are discussed, Section II contain the related works and discusses the Image segmentation methods for human pathologies diagnosis. Section III concludes research work with future directions and references.

II. IMAGE SEGMENTATION METHODS FOR HUMAN PATHOLOGIES DIAGNOSIS

Clustering is the process of making objects of similar characteristics into a group. A cluster group objects or elements are usually homogenous. Different objects are selected for different clusters according to their characteristics and each cluster vary from each other based on its size and other features. Clusters are heterogeneous in nature with each other cluster. Clustering process may be uncertain and cumbersome. Clustering is classified into hard and fuzzy clustering. In the case of hard clustering, each and every object is allocated to only one single cluster during the procedure. In the fuzzy clustering mechanism the data or instances are allocated to two or more clusters and a degree of membership is also associated with them accordingly. This degree of membership is based on the association of data with other clusters.

Nishchal K. Verma et al proposes Improved Mountain Clustering version-2 (IMC-2) which is an advancement of IMC-1. He claims that the proposed medical image segmentation methodology is better in several aspects compared to that of traditional FCM and K- means algorithm. This segmentation is used on the diagnosis based on medical images, such as MRI and x-rays of dental, chest and used to identify/diagnose disease such as lung cancer, tuberculosis, dental problems, tumours and so on [3].

Annemie Ribben et al presented a framework which aims to identify the relationship between the object and the attributes and map them accordingly. This mapping is done extensively for analysing the brain MRI image which are of large sets and heterogeneous too. In addition to this, it performs image segmentation and clustering process in parallel, to divide the instances into subgroups [4]. In the case of lung disease diagnosis, the pulmonary nodules are the primary factor to be considered. It gives a clear picture for identifying lung cancers. The ground glass opacity and juxta vascular nodules are considered to have a wide scope of research.

The details of the pulmonary nodules boundary are tedious to obtain from the existing segmentation method. The co-efficient of the curvature is taken as the base for the process of fuzzy clustering in process of pulmonary nodules segmentation in order to address the above said issue.

Hau-Lee Tong et al proposed a method for analysing the CT brain images through segmentation. Two methods of segmentation are proposed in this work which are modified FCM with population-diameter independent (PDI) and expectation-maximization (EM) segmentation. The obvious goal is to get a clear picture of the brain ventricles and analyse them through the acquired result. One of the above said techniques has been used for this purpose [5].

The model deformation strategy and statistical shape model has been a part of ASM [19]. In this the information of the object shapes are extracted and represented precisely. Precise segmentation has been an important motive in Wuxia Zhang et al approach. In order to obtain segmentation precisely manifold learning techniques was used in this approach. Shape priors could differ from one patient to another, so patient specific shape priors are estimated. This is assimilated to a deformable model based framework for the purpose of segmentation.

Medical image analysis has many different approaches and techniques where, CNNs (Convolutional neural network) was one of them which became popular for its unique methodology. Unlike the classic machine learning methods the CNN uses the training data to enhance the set of kernels where the classic machine learning methods would use Gaussian kernels or some predefined kernels. Learning process is an important aspect in this regard [24, 26]. Information extraction by the system is done automatically and specifically which is required for a particular task. Classes' differentiations are done through learning process (for knowing the image's spatial and intensity information) by the provided information. This scenario is more like a homosapien observing and identifying the objects in a medical image.

For processing brain images segmentation, the CNN is exclusively utilized. Pim moeskop et al uses CNN to cross co-relate and automate the segmentation of the brain images into classes of tissues. This uses multiple patch and convolutional kernel sizes to ensure the spatial stability and have a precise segmentation details. This is also used to acquire multiple information about each voxel [8]. Alexey A. Novikov et al [25] uses CNN architecture for chest radiograph segmentation which is performed in multi class levels.

A novel segmentation procedure has been proposed by Shihab A. Hameed et al. It has been idiosyncratically developed for medical image segmentation. A hybrid segmentation process has been carried out in this context, where, the threshold segmentation with reckoning implementation and correlation matching with adjacent regions takes place. With the visual context and information, certain details can be acquired in an image and some cannot be acquired. In that context, the threshold points can be chosen which can be multiple points based on the visual witness and information. The correlation matching is done in the regions, where the boundaries are visually indistinct.

Topology problems have been addressed by Xin-Jiang et al, where an efficient method termed to be as level set method has been proposed. Previous methods and algorithms could not deal with the evolution of curves. The level set method is used by many segmentation algorithms in recent times [10]. Redouan Korchiyne et al used multifractal analysis for segmentation (medical image) which is considered to be robust .When there is a requirement to segment large volume of datasets and characterize the image based on tissue and bone types, the traditional segmentation method would be unwieldy. Automated image segmentation would evict the aforesaid issues and hastens the process [11].

Region-based active contour models, gives a framework of variation image segmentation, tend to be relied on intensity homogeneity in every regions of the image to be segmented. To identify and find those regions, computer aided curves or active contour or snakes moves within the image. The location and shape of the snake in the image is used as the information for depicting the snake model energy which may vary with respect to the image properties. A higher level image criteria analysis is used to define the external force, whereas, the shape of the snake is used to define the internal force. The snake N(s) defined as $N(s) = (x(s), y(s))$, where $x(s)$and $y(s)$ be the x, y -coordinates are related with contour [20].

Intensity inhomogeneity is often in medical images, where, Guodong Wan et al proposed an active contour model which works perfect with intensity inhomogeneity absence. The reason behind that is the information of weak edges is disturbed by the heterogeneous intensity. Edges enhancement has to be done on that context to overcome the overhead.

Forming of larger regions from sub-regions and pixels is known as region growing. Seed points are used by the region growing algorithms where, they append to each seed point, its neighbouring pixels with similar characteristics and grow their regions. Region growing is comprised of two steps which are i) Defining the homogeneity criteria and ii) Selecting process of the seed points.

The finding of seed points can be done both manually and also has an automatic mechanism in which it selects the pixels based on the criteria of satisfying some features of the selected regions. The region growing algorithm has a step by step procedure which works in an orderly fashion. The steps are (i) Choosing the seed pixel (ii) Neighbouring pixel checking (add them to the region if they have similarities to the seed) and (iii) Repeating the step (ii) for every new pixels added. Keeping in consideration on implementation, then the region growing algorithm is very easy and efficient too. Particularly for the regions which have homogeneity intensities, it can give a clear-cut segmentation.

For ultrasound images, an automatic segmentation procedure has been proposed by Harjot Kaur Gill et al. It is based on the region growing mechanism which involves in the automatic seed selection which has several advantages over the manual seed selection process. The main challenge in the ultrasound image segmentation is the identification process of the abnormal boundaries. The automatic seed selection process facilitates to locate the presence of the abnormal boundary regions without any delay or difficulties [15].

Wavelet transform have the ability to refrain from the noises in an image when it has a large scale. It is being widely used and has become popular in recent times. Wavelet scales have different impacts on the image when it is either smaller or larger. When the wavelet scales are smaller, stronger becomes the capability of the image extracting process. In the process of multi scale edge detection of an image, the segmentation process which is based on the wavelet transform being a multi-scale analysing tool is used. The changes in the feature of the image gray level are signalled by the points of the histograms and its sudden changes in the peak and the valley levels.

The wavelet transform is used to identify the threshold of the histogram. It uses the singular point and the extreme point by detecting them to define the features of the peak point of histogram. The Multi-scale feature of the wavelet transform facilitates to identify the threshold of an image in segmentation. From the lower resolution level to the higher resolution, the segmentation procedure can be carried out in multiple hierarchy thresholds in a medical image's histogram. This is ultimately because of the multi-scale and resolution feature of the wavelet transform. The zero-crossing point of wavelet transform $W_{2^j} H(x)$ expresses the low-pass signal. The sudden change points and the minute details of the gray value are identified in the case, when there is increment in the local details of the signal due to the decrement of the 2^j scale [16].

The process of extraction of objects from a background involves in selection of a threshold T which is done by the thresholding approach. This T threshold is selected based on the image of histogram. Pixels are classified according to the selected threshold T in such a way that, the pixels intensities are considered for grouping them. The larger pixel intensity when compared to the T is classified into a group, while the smaller pixel intensities, i.e. the intensity of the pixels which are lesser than the defined threshold is classified into another group. The pixel intensities which are distributed throughout the image are the cause for selecting the threshold which is the primary process in a threshold algorithm.

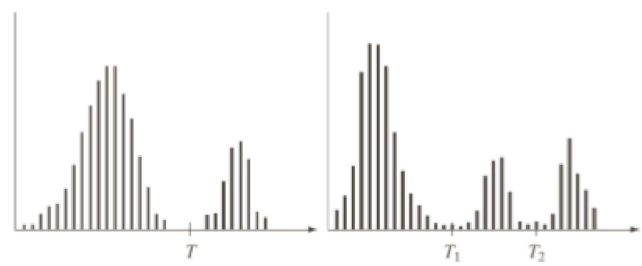

Figure 2. Choosing the threshold (Single threshold and Multi threshold)

In the above-mentioned thresholding process, the algorithms for thresholding can be segregated into two types. They are termed to be as local and global thresholding. The quality of having a uniform and constant threshold T, for each and every pixel in the image is termed as global thresholding. In Contrast, the threshold T which is being contingent upon the properties of the image or a particular region in an image, pixels average intensity, are known as local thresholding. To obtain a 3D model of an image, the segmentation plays a pivotal role there. In that motive, Cheol-Hwan Kim et al [1] proposed an adaptive segmentation algorithm. The boundaries of object can be identified efficiently by the process of adaptive thresholding, but it gets deviated in flat region surface. Voxels at the object boundary regions encounter a procedure of being calculated their threshold value.

This adaptive threshold value is calculated by the histogram, where the intensities of the voxel are distributed over the histogram in a 3D window. To have a smooth application, the 3D Gaussian kernels are used to weigh the voxels in the 3D window before they hoard to the histogram [17].

The formula for histogram equalization:

$$s_k = T(r_k)$$
$$= (L-1)\sum_{j=0}^{k} P_r(r_j)$$
$$= (L-1)\sum_{j=0}^{k} \frac{n_j}{n}$$

Lung image segmentation is the problem undertook by Wei. Y. et al. in which, they developed a system termed as structured edge detector.

This is used for the boundary and edge detection process which detects more efficiently and effectively. Training process has been undergone ahead of time in the structured edge detector for detecting the boundaries in CXR where the lung fields are delineated manually. From the marked boundary, an ultra-metric contour map (UCM) has been generated. This contour map is used for excerpting the Lungs contour by identifying the contours in UCM having high confidence level [21].

As discussed before, the Convolutional neural network amalgamated with deep learning have produced contemporary results in the automated medical image segmentation. Reiterative deep learning has been used by Jung uk kim et al. for medical image segmentation. In order to show efficient segmentation results which helps in localization of the region of interest accurately, that includes complex shape and textures, a reiterative learning process and encoder-decoder network are practised in this methodology [22, 24].

The morphology technique facilitates to have the capacity for having a control to manage the disparity in the image data. A kernel (Structuring element) of capricious shape and dimension gives a set operation which is the rudimentary morphological operation. Dilation is an operation that grows or thickens objects in a binary image. Dilation is defined in terms of set operations. The Mathematical definition of dilation A and B is shown in (1), which follows below.

$$A \oplus B = \{z|(B)_z \cap A \neq \emptyset\} \quad (1)$$

Erosion is an operation that shrinks or thins objects in a binary image. The erosion of A and B is shown in (2), which follow below.

$$A \Theta B = \{z|(B)_z \cap A^c \neq \emptyset\} \quad (2)$$

Based on the structuring element, the dilation process will facilitate the objects to proliferate in size. The amalgamation of dilation and erosion is being defined for all the additional morphological operations [23]. The organ tissue segmentation process in the medical image is a challenging task where, hongya lu et al used the convolutional neural network which is based on a dual tree complex wavelet transform (WCNN). The traditional pooling is merged with a dual tree complex wavelet pooling in a convolutional neural network.

Precise texture recognition and scalability of image in spatial direction is achieved through wavelet decomposition. In WCNN, the image is dispersed to a number of wavelet sub-bands, where, the higher frequency sub-bands are filtered which enables to decrease the data noises [26].

III. Conclusion

Various segmentation techniques in medical imaging related to cancer, blood cell counting, lung diseases and many more diseases has been analysed in this paper. At present the cluster-based method and atlas-based segment method produces the effective outcomes. So, the cluster-based segmentation techniques. The major disadvantages in medical image segmentation are noted as image quality and number of errors. So, these errors have to be improved for effective segmentation.

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