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Overview of Medical Image Segmentation

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ABSTRACT
This paper reviews image segmentation as related to medical image processing. It examined fundamental medical image processing flow of actions, reviews available segmentation methods in literatures, their applications and brief performance. It conclusively highlight the need for development of a robust medical image segmentation method which will be able to recognize malignant growths in human body before it gets out of hand. The problem of cancerous growth as a threat to human existence is emphasized.

Keywords: Image processing, medical images, image segmentation, image enhancement

I. INTRODUCTION

American Heritage Dictionary, 3rd edition: a reproduction of a person or an object, especially a sculptured likeness. A physics philosophy where an optically formed duplicate, counterpart, or other representative reproduction of an object, especially an optical reproduction of an object formed by a lens or a mirror [1]. Medical imaging systems are based on the physical interaction between some energy source and the human body. Exceptions include phonocardiography and thermography, which use internal energy sources within the body are rare and represent very few applications. Literatures have identified many medical imaging modalities [2; 3]. These modalities include: radiology and computed tomography with X-ray, diagnostic ultrasound, magnetic resonance imaging, radioisotope imaging, and electrical impedance tomography.

II. MEDICAL IMAGE PROCESSING

Image processing in medical diagnosis involve stages such as image capture, image enhancement, image segmentation and feature extraction [4:5] Figure 1 shows a general description of lung cancer detection system that contains four basic stages. The first stage starts with taking a collection of image (normal and abnormal) from the available client. The second stage applies several techniques of image enhancement, to get best level of quality and clearness. The third stage applies image segmentation algorithms which play an effective rule in image processing stages, and the fourth stage obtain the general features from enhanced segmented image which gives indicators of normality or abnormality of images.

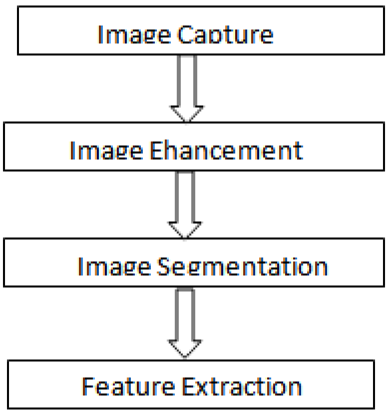

Figure 1: Lung Cancer image Processing Stages

III. MEDICAL IMAGE SEGMENTATION

The aim of segmentation is to extract region of interest (ROIs) containing all masses and locate the suspicious mass candidates from the ROI. Segmentation of the suspicious regions on a mammographic image is designed to have a very high sensitivity and a large number of false positives acceptable since they are expected to be removed in later stage of the algorithm [6] Researchers have used several segmentation techniques and their combinations also. Segmentation is very crucial in image processing; its output will determine the effectiveness of the features to be extracted at the feature extraction stage [7] The outcome of these extracted features will be used in guiding the decision of medical personnel [8]

3.1 Thresholding Techniques

Global thresholding [9] is one of the common techniques for image segmentation. It is based on the global information, such as histogram. The fact that masses usually have greater intensity than the surrounding tissues can be used for finding global threshold value. On the histogram, the regions with an abnormality impose extra peaks while a healthy region has only a single peak [10] after finding a threshold value the regions with abnormalities can be segmented. Global thresholding is not a very good method to identify level. Global thresholding has good results when used as a primary step of some other segmentation techniques. Local thresholding is slightly better than global thresholding. The threshold value is defined locally for each pixel based on the intensity values of its neighbor pixels [11] Multiple pixels belonging to the same class (pixels at the periphery of the mass and pixels at the center of the mass) are not always homogenous and may be represented by different feature values. Li and his associates used local adaptive thresholding to segment mammographic image into parts belonging to same classes and an adaptive clustering was applied to refine the results[12]

` Matsubara's group [13] developed an adaptive thresholding technique that uses histogram analysis to divide mammographic image into three categories based on the density of the tissue ranging from fatty to dense. ROIs containing potential masses are detected using multiple threshold values based on the category of the mammographic image. Dominguez and Nandi [14] performed segmentation of regions via conversion of images to binary images at multiple threshold levels. Images in their study, with grey values in the range (0, 1), 30 levels with step size of 0.025 were adequate to segment all mammographic images. Varel segmented suspicious regions using an adaptive threshold level [15] The images were previously enhanced with an iris filter. Li [16] used adaptive gray-level thresholding to obtain an initial segmentation of suspicious regions followed by a multi-resolution Markov random field model-based method.

3.2 Region-Based Techniques

Markov random field (MRF) or Gibbs random field (GRF) is one of the segmentation methods in iterative pixel classification category. MRFs/GRFs are statistical methods and powerful modeling tools [16] Szekely [17] used MRF in fine segmentation to improve the preliminary results provided by the coarse segmentation. In coarse segmentation the feature vector is calculated and passed to a set of decision tress that classified the image segment. After the fine segmentation they used a combination of three different segmentation methods; a modification of the radial gradient index method, the Bezier histogram method and dual binarization to segment a mass from the image.

Region growing and region clustering are also based on pixel classification. In region growing methods pixels are grouped into regions. A seed pixel is chosen as a starting point from which the region iteratively grows and aggregates with neighboring pixels that fulfill a certain homogeneity criterion. Zheng [18] used an adaptive topographic region growth algorithm to define initial boundary contour of the mass region and then applied an active contour algorithm to modify the final mass boundary contour.

Region clustering searches the region directly without initial seed pixel [11] pappas [19] used a generalization of k-means clustering algorithm to separate the pixels into clusters based on their intensity and their relative location. Li [12] used adaptive clustering to refine the result attained from the localized adaptive thresholding. Sahiner and his research group [20] used k-means clustering algorithm followed by object selection to detect initial mass shape within the ROI. The ROI is extracted based on the location of the biopsied mass identified by a qualified radiologist. initial mass shape detection is followed by an active contour segmentation method to refine the boundaries of the segmented mass.

3.3 Edge Detection Techniques

Petrick used Laplacian of Gaussian filter in conjunction with density weighted contrast enhancement (DWCE) [21]. DWCE method enhances the structures within the mammographic image to make the edge detection algorithm able to density.

Edge detection algorithms are based on the gray level discontinuities in the image. Basis for edge detection are gradients or derivatives that measure the rate of change in the gray level. Rangayyan [22] described standard operators for edge detection such as Prewitt operator Sobel operator, Roberts operator and Laplacian of Gaussian (LoG) operator. Fauci et al. [23] developed an edge-based segmentation algorithm that operative procedure, a ROI Hunter algorithm for selecting ROIs. ROI Hunter algorithm is based on the search of relative intensity maximum inside the square windows that form the mammographic image. Zou [24] proposed a method that uses Gradient Vector Flow field (GVF), which is a parametric deformable contour model, after the enhancement of mammographic images with adaptive histogram equalization, the GVF field component with the larger entropy is used to generate the ROI. In the example of GVF with and without enhancement is given.

Ferreira [25] used active contour model (ACM) based on self-organizing network (SON) to segment the ROI. This model explores the principle of isomorphism and self-organization to create flexible contours that characterizes the shapes in the image. Yuan [26] employed a dual-stage method to extract masses from the surrounding tissues. Radial gradient index (RGI) based segmentation is used to yield an initial contour close to the lesion boundary location and a region-based active contour model is utilized to evolve the contour further to the lesion boundary.

3.4 Hybrid Techniques

Stochastic model-based image segmentation is a technique for partitioning an image into distinctive meaningful regions based on the statistical properties of both grey level and context images. Li [27] employed a Finite Generalized Gaussian Mixture (FGGM) distribution which is a statistical method for enhanced segmentation and extraction of suspicious mass area. They used FGGM distribution to model mammography pixel images together with a model selection procedure based on the two information theoretic criteria to determine the optimal number of image regions. Finally, they applied a contextual Bayesian Relaxation Labelling (CBRL) technique to perform the selection of the suspected masses.

Ball and Brue [28] segmented suspicious masses in polar domain. Adaptive Level Set Segmentation Method (ALSSM) was used to adaptively adjust the border threshold at each angle in order to provide high-quality segmentation results. The work was extended in [28], where Speculation Segmentation with Level Sets (SSLS) was used to detect and segment speculated masses. In conjunction with level set segmentation, Dixon and Taylor line operator (DTLO and a generalized version of DTLO (GDTLO) were hybridized.

Hassanien and Ali develop an algorithm for segmenting speculated masses based on Pulse Coupled Neutral Networks (PCNN) in conjunction with fuzzy set theory [29].

IV. LITERATURE REVIEW

[30] summarized method of medical image segmentation. They divided into three generations. the first generation is composed of the simplest forms of image analysis such as the use of intensity thresholds and region growing. The second generation is characterized by the application of uncertainty models and optimization methods, while the third generation incorporates knowledge into the segmentation process. Some medical image database foe segmentation method validation were identified which include McConnell Brain Imaging (MNI) Internet Brain Segmentation Repository (IBSR) Section for Biomedical Image Analysis (SBIA).[31] summarised new method for medical image segmentation which is called the status Quo of Artificial Intelligence method in Automatic medical image segmentation. Since segmentation is an effective and fundamental step in the medical image analysis (MIA). It is categorized into four segmentation method based on applied AI techniques. These methods can decrease the human intervention gradually and each category facilitates the higher level of AI techniques than the previous one. They are respectively based on image processing techniques, hybrid AI methods, expert systems development and ultimately registration-based in the multispectral and multi model imaging.

[32] summarized eight different deformable contour methods (DCMs) of snake which are Balloon snake, Topology snake, Distance snake, Gradient vector flow snake Original level set, Geodesic active contour, Area and Length active contour and Constrained Optimization and level set method applied to the medical image segmentation are presented. These DCMs are now applied extensively in industrial and medical image application. The segmentation task that is required for biomedical application is usually not simple. The studied DCMs are compared use both qualitative and quantitative measures and the comparative results both the strength and limitation of these method. So from this medical segmentation comparison can also be translated to other image segmentation domains.

Xiaolei and Gavrii, in their research efforts, have been devoted to processing and analyzing medical image to extract meaningful information such as volume, shape, motion of organs in other to detect abnormalities and to quantify changes. They also performed image data immense practical in medical information. Medical image such as computed Axial Tomography (CAT), Magnetic Resonance Imaging (MRI), Ultrasound, and X-Ray, they focus on two general categories of segmentation methods which are widely used in medical visions, namely the deformable models and the machine learning-based classification.

Zulaikha and Mohamed developed a robust segmentation approach for noisy medical image segmentation using Fuzzy Clustering with spatial probability [33] This developing robust and efficient algorithm for medical image segmentation has been a demanding area of growing research interest. Fuzzy C-Means (FCM) algorithm was extensively used in medical image segmentation. FCM is highly sensitive to noise because it segment images on the basis of approach which utilizes histogram based fuzzy C-means clustering algorithms for the segmentation of medical images. So to improve the robustness against noise, the spatial probability of the neighbouring pixel is integrated in the objective function of FCM. The noisy medical are de-noised with the help of an effective de-noising algorithm, prior to segmentation. The results obtained from the experimentation showed that the proposed approach attains reliable segmentation accuracy despite of noise levels and it is also clear that the proposed approach is more efficient and robust against noise when compared to that of the FCM.

Rastgarpour and Shanbehzadeh identified biomedical features for segmentation which are more accurate by applying the artificial intelligence methods in which include intelligence methods in valuable medical image segmentation [34]. This segmentation method depends on many factors like disease type and image features and those factors result in remain the segmentation challengeable and lead to increasing the growth of literatures. The literatures help the researchers to understand more easily and rapidly and then a novel categorization is proposed related to the most recent important literatures in four sets based on applying the AI techniques and decreasing human intervention. Categorization of available methods and literatures. The segmentation methods depend on modality and dimension of imaging because of the high dependency on factor like disease type and image features. Adegoke and his research group conducted an extensive survey on image segmentation but it was basically on iris segmentation as it is related to development of iris recognition system [7]

V. CONCLUSION

Increased development of malignant and recorded death rate of men and women in the 21st century [35:36:37] necessitates development of real-time, robust segmentation algorithms which will be able to detect development of growths in human body. It was discovered from literatures that early detection in malignant such as ovarian cancer [38] colorectal cancer, breast cancer [39], prostate cancer [40] and other abnormal developments in human systems at early stage can be helpful to their control [36:41]

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