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A Novel Active Contour Model for Segmentation of Lungs in Chest Radiography

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ABSTRACT
Lung Segmentation in Chest Radiographs needs more attention. The proper selection of Lung Segmentation algorithm with high precision and low bias is a challenging task in the diagnosis of abnormalities in the Lung using Computer Aided Diagnosis. In this work Segmentation of lung is carried out using a noveldeformable shape approach. The novel deformable technique involves the Active contour model with local bit method.The Segmentation result obtained from thisproposed method is compared with the Ground Truth image of the standard database using various evaluation Metrics such as Dice Coefficient and Jaccard'scoefficient. Based on the evaluation the proposed model provides a segmentation accuracy of nearly 96%. Many parameters are calculated to validate the proposed segmentation algorithm with the other algorithm.
KEYWORDS: Computer Aided Diagnosis, Chest Radiography, Active Contour Model, local binary fit, deformable shape model.

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I. INTRODUCTION

Chest Radiography (CXR) imaging is normally used to make a diagnosis of lungs, heart, ribs and thoracic region. In this paper CXR imaging is used to find the different abnormalities in the Lungs. The Segmentation of Lung plays an important role in finding the abnormalities. Segmentation of the image is mainly divided in to two types one is based on similarity based method such as Thresholding and Region growing and merging another one is based on discontinuity which constitute isolated points, Lines and edges. The Lung Segmentation in CXR can be done by using three methods i) Rule Based ii) Pixel Based and iii) Deformable based [1]. In this research Novel segmentation method is proposed by fusing Active Contour Model, a deformable based approach with deep learning algorithm method to improve the accuracy of Segmentation.

Deformable model is one of the effective methods of segmentation when we are considering the shape parameter as the constraint for segmentation process. Usually the medical images are corrupted by noise, in such cases the identification of the region of interest is a difficult task by using the rule based method like iterative thresholding and by using pixel based method in such applications deformable model which is a shape based approach plays an important role. In CXR the segmentation of lung region is a very important task because the shape of the lung region is also one of the parameter to be considered in finding the lung abnormality. In general deformable models are represented as curves. The curve is formed by joining different points called control points [2]. Deformable Active Contour method is not applied to the image as a whole but it is concerned only with the region of interest to be segmented. Active contour model employs both edge based and region based approach for segmenting the region of interest. Active Contour is a dynamic technique, where an initial estimate is made, either by instituting a large contour that may contract or a small contour that may expand until its shape matches the region of interest to be segmented [3]. The contour is a dynamic one which has two energy functions one is the external energy and other one is the internal energy. The internal energy denotes the elasticity which is required for the contour to expand or contract and bending energy which eliminates the occurrence of sharp corners or spike in the image. The external energy operates on the image pixel intensity. The sum value of internal energy and the external energy makes the curve to converge to its energy minima.

This paper is organized as follows, Section ii review the different Active contour model (ACM)in the literature, section iii deals with the Materials and methods used in this paper, Section IV deals with the results and discussion. Section v deals with conclusion and future work

II. REVIW OF DIFFERENT TYPES OF ACTIVE CONTOUR MODEL

Active contour model gain its popularity in the late 80's after the work carried out by kass M in 1988 [4] in which contour is considered as a snake, a energy minimizing spline guided by external force and image force. The forces guide the snake to reach the region of interest. However this method sometimes misses the region of interest. To overcome this difficulty Cohen D [5] proposed a model in which external forces are modified so that curve behaves like a balloon. A geometric ACM proposed by V caselles [6] is used to find smooth shape and extract the contours simultaneously. An improvement in the geometrical model is again done by V caselles [7] that is geodesic ACM which gives stable boundary detection when there is a large variation in the gradients. To improve the convergence rate and initialization problem of traditional snake Gradient Vector Flow(GVF) model [8] was developed by ChenyangXu. ACM without edges was developed by Tony F.chan [9] in which gradients are not used to represent the boundary. Geometric ACM using prior shape model was developed by Yunmei Chen [10] which makes the contour to identify the region of interest even though the boundary is not visible. Level set based ACM was developed by Tony chan [11] in which fusion of prior shape model and image intensity is carried out which gives the privilege of translation, scaling and rotation of prior shape model.Legendre moment with ACM is another method developed by Yan Zhang [12] used for the region of interest segmentation in the noisy environment. Curvelet based geodesic snake was proposed by haoshan [13] to detect multiple objects in the noisy environment and Another multiple object segmentation technique was Proposed John A.Bogovic [14] which is mainly used for organ segmentation in medical images. A new region based ACM was developed by yang xiang [15] in which velocity for moving curves is calculated using fast Fourier transform. A hybrid region and edge based approach for ACM with Genetic Algorithm [16] for parameter tuning is used for segmentation of Medical images. Graph cut based Geodesic Active contour was developed by DongshengJI[17] which provides good convergence and provide with global result for segmentation. Multiple Active Contour with particle Swarm optimization [18] and Active contour with Multiswarm particle optimization with inertia adjustment using fuzzy rules [19] provide image segmentation with good energy minimization when compared to the traditional snake algorithm. Deep learning with active contour developed by Christian ruppercht [20] provide an interactive boundary extraction Method. Integrating Machine learning with region based Active Contour Model [20] provide simple feature vector and it is insensitive to parameter tuning. Different ACM techniques used for segmentation of images are surveyed and their characteristics are studied based on that in this paper a Novel Active contour Model was proposed to segment the lung region in the chest radiography.

III. MATERIALS AND METHODS

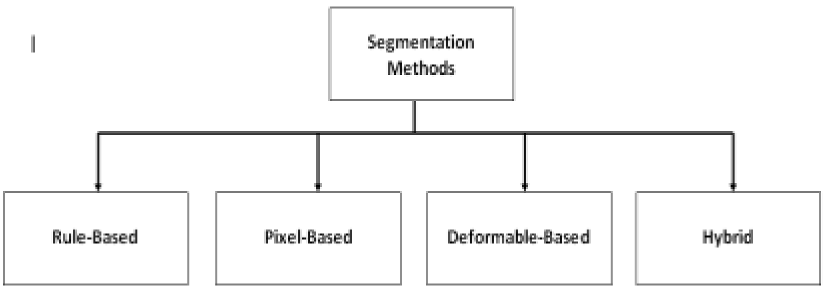

Figure: 3.1 Segmentation Methods

In this paper to validate the proposed algorithm the standarddatabases are used i) Japanese Society Radiological T(JSRT) database[21] ii) Montgomery database a standard digital image database for Tuberculosis is created by National Library of Medicine which consist of 80 normal cases and 58 cases with Tuberculosis findings[22]. For this two databases ground truth image was available and the Lung region segmented by the proposed method is compared with the ground truth image of the standard database using different evaluation metrics. The are different Segmentation method as shown in fig.1. The Proposed Method is compared with Pixel based method Otsu's thresholding and rule based method Marker Controlled Watershed Segmentation.

3.1 Otsus'sThresolding:

In this method thresholding is done by considering the histogram of an image [23] . This method is suitable for the images which are less corrupted by noise. If the image is superimposed by noise then there is a possibility of segmentation error. Hence this method when applied to CXR images for lung segmentation will not give fruitful results.

3.2 Marker Controlled Watershed Segmentation:
Marker – Controlled Watershed Transform is a Rule based approach. The internal and external Markers are defined. A Marker is a connected component belonging to an image. The Markers which are connected component do possess the same intensity values and are treated as regional minima [24]. Internal Markers are used to limit the number of regions by specifying the object of interest. External Markers are used to mark the background. Watershed algorithm is used to do the Segmentation. The lung region Segmented by this method suffer from Over Segmentation.

3.3 A Novel Deformable based Active Contour Model for the Lung region Segmentation
ACM are generally categorized in to two types parametric based ACM and Geometric based ACM. The ACM

3.3.1. Parametric Based Model:

In parametric based active contour method the contour is represented as a parametric form. The parametric model doesn't adapt to the topological changes in the image. The parametric contour can be formed based on two considerations that is energy minimization technique in which summation of external energy which deals with the force that make the contour to attract toward the object boundary to be segmented and internal energy which deals with the elasticity and bending force which deals with static problem and the next one is based on dynamic force formulation.

3.3.1.1 Parametric method based on Energy Minimization Technique:

The contour is defined in the (x, y) plane of an image as a parametric curve in equation (1) as

$$P(c) = (x(c), y(c)) \tag{1}$$

The internal energy are written as small changes in the position of P(c) of each point on the contour, the parameter 'c' being the arc length along the contour boundary.

The parametric curve possesses both the elastic and bending energy. The curve expands or contract by introducing tension. The Elastic energy and the bending of the parametric curve is given in equations (2) and (3) respectively.

$$E_{elastic} = \frac{1}{2}\int \alpha\,(c)|P_c|^2\,ds\ , \quad P_c = \frac{dP(c)}{dc} \tag{2}$$

$$E_{bending} = \frac{1}{2}\int \beta\,(c)|P_{cc}|^2\,ds\ , \quad P_{cc} = \frac{d^2P(c)}{dc} \tag{3}$$

P_c and P_{cc} are the first and second order derivative of the curve. The term α(c) and β (c) allow the parametric curve to control the elastic energy and bending energy on different points of the contour. In some application α (c) and β(c) is consider to be constant.

The external energy may vary depend on the image we are considering for the application. Generally it includes energy terms of edges, lines and terminations as show in equation (4).

$$E_{image\ \ constraint} = w_{line}\,e_{line} + w_{edge}\,e_{edge} + w_{term}\,e_{term} \tag{4}$$

$W_x$denotes the weight of line, edge and termination. By adjusting the weight various range of contour can be obtained.

3.3.1.2 Parametric method based on formation of dynamic force:
The parametric model using energy minimization technique was considered as a static problem but this method is not suitable to handle the dynamic way of forming a contour. Hence the parametric method based on the formation of dynamic force was considered. This method is based on Newton's second law.
The Parametric model has two limitations:

i) If the targeted object and initial contour shape widely vary then the different parameter curve has to be consider for finding the object boundary
ii) Deparametrization results in computational overhead.

To overcome this disadvantage the geometric based active contour method was considered.

3.3.2 Geometric based active contour Model (GACM):
This method of active contour method adapts to the topological changes which is not possible with the parametric model. It provides a wide area of application mainly for medical image segmentation due to its adaptation to the topological changes. This model mainly based on curve evolution theory and level set method [3]. This method involves the internal and external geometric measures. GACM is mainly based on level set framework and curve evolution theory. Since GACM depends only on the geometric measures for evolution of contour, reparametrization is not frequently and adapts the topological changes. Geometric contour formation depends on equations (5) & (6)

$$\varphi_t = c(R + l_o)|\nabla\varphi| \tag{5}$$

R is the curvature, l_o is a constant

$$c = c(x) = \frac{1}{|\nabla(G_\sigma(x) * I(x))|} \tag{6}$$

In equation 8 $c(R+l_o)$ reveals the overall speed of level set. The curvature R is responsible for the smoothness of the curve whereas l_o value is used to expand or contract the curve [9]. However this geometric ACM will have a boundary leaking problem. To solve this problem many contour evolution stopping method has been evolved.
In the proposed method a adaptive local binary fitting (LBF) method with a Gaussian kernel function is used that enables the extraction of accurate local image information. In this adaptive model the contour evolution is guided by the local fit term of the image and also the area. The bias field approximation is done by varying the Gaussian kernel function. This method is well suited for lung segmentation in CXR when compared to other segmentation technique.

IV. RESULTS AND DISCUSISON

The result of the various segmentation algorithm is discussed here. The Lung region Segmentation in CXR using Otsu's thresholding & Marker Controlled Watershed Segmentation is shown in Fig.4.1a & b respectively. The result of the proposed segmentation technique, Novel ACM is shown in Fig.4.2 (a,b&c).
The proposed Method was validate using four Segmentation Parameter for determining the accuracy of Segmentation such as Sensitivity, Specificity, Dice Coefficient and Jaccard index.

Sensitivity: Sensitivity is the measure of number of actual positives which are correctly segmented.. It is defined as the ratio of

$$sensitivity = \frac{TP}{TP + FN}$$

Specificity: Specificity is also defined as the True Negative Rate.

$$specificity = \frac{TN}{TN + FP}$$

Jaccard's Index: It is also known as intersection over union. Jaccard similarity coefficient is a statistics used for comparing the result of segmentation (A) with the ground truth image (B) in the database.

$$J(A, B) = \frac{A \cap B}{A \cup B}$$

Dice Coefficient: This parameter is also used to find the similarity exist between the segmented output and the ground truth image

Figure : 4.1a) Otsu's Thresholding

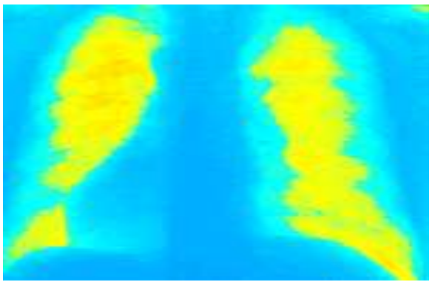

Figure : 4.1b) Marker Controlled Segmentation

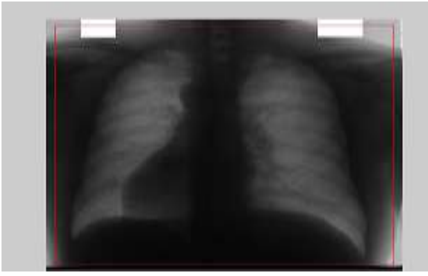

Figure : 4.1c) Initial Contour

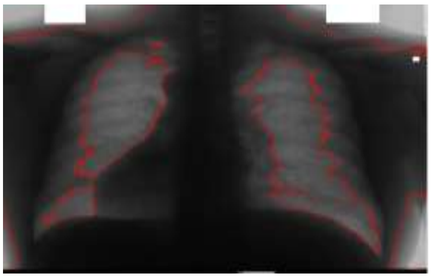

Figure : 4.1d) Contour Evolution

Figure : 4.1d) Contour Evolution

Table 4.1. Analysis of segmentation methods:

Segmentation Parameters	Otsu Method	Marker Controlled Watershed	Proposed ACM
Senstitivity	.7877	.7960	.851
Specifity	.9643	.9723	.9857
Jaccard index	.7147	.7080	.9412
Dice Coefficient	.8179	.8121	.9533

V. CONCLUSON AND FUTURE WORK

Lung Segmentation plays an important role in identification of any lung diseases. In this paper a novel segmentation techniques is developed and applied to the standard CXR database. Four Parameters are calculated and it is compared with the segmentation methods in the literature. The method discussed in this work outperform when compared to the other method. The proposed method produces nearly 96% accuracy in segmentation of lung region. Further this method can be improved by decreasing the number of iterations and by increasing the accuracy.

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