



A Study on Lung Segmentation for the Detection and Diagnosis of Lung Cancer

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Abstract— Lung Segmentation is a crucial part of both Computer Aided Detection system and Computer Aided Diagnosis system for lung cancer because the performance of those systems are depended on the performance of the Lung Segmentation. This paper presents a study on the existing Lung Segmentation methods, research challenges and their future prospects.

Keywords— Lung Segmentation, Computer Aided Detection, Computer Aided Diagnosis, Lung Cancer.

I. INTRODUCTION

Lung Cancer is one of the most serious problem causing death in the world. Compare to other diseases, cancer tends to have high death rate and treatment of cancer is effective only on its early stage. As per American Cancer Society's publication, Cancer Facts & Figures 2016 [1], lung cancer is the most leading cancer death which estimated about 158,080 deaths for the year 2016 in U.S.A alone. If the cancer can be detected on its early stage, then there is a good chance of survival of the patient. Usually Computed Tomography (CT) or Low-Dose Computed Tomography (LDCT) is used for early detection of cancer. Radiologists examine the image projected as slice by slice of the whole thorax anatomy and detect cancer cells present in the lung. Since it is a tedious work which requires a very minute examination, there is a very high chance of erroneous detection. Hence an automated system is required to detect very small and subtle pulmonary nodules of lung cancer. This detection of cancer can be performed by using Computer Aided Detection (CADE) system and the diagnosis of detected pulmonary nodules by Computer Aided Diagnosis (CADx) system.

Generally, Computer Aided Detection (CADE) system consists of two processing steps: Lung Segmentation and Nodule Detection. For Computer Aided Diagnosis (CADx) system, there are two processing steps: Nodule Segmentation and Nodule Diagnosis. Lung Segmentation extracts both left and right lungs from Computed Tomography (CT) scan image by suppressing background details. From the segmented lungs, pulmonary nodules are detected in Nodule Detection step. The detected pulmonary nodules are segmented in Nodule Segmentation step of CADx system. The segmented nodules are diagnosed by analysing their growth rate and appearance to classify them as malignant or benign nodules in Nodule Diagnosis step. Since Lung Segmentation is the first processing step of lung cancer detection and diagnosis system, the performance of the whole system depends on the accuracy and sensitivity of Lung Segmentation. In this paper, we focus only Lung Segmentation Methods (Section II), Research on Lung Segmentation (Section III), Research Challenges and Future Prospects (Section IV). Finally we provide conclusion of this paper.

II. LUNG SEGMENTATION METHODS

Lung Segmentation is the first processing step for both Computer Aided Detection (CADE) and Computer Aided Diagnosis (CADx) for lung cancer. Since the performance of both CADE and CADx depend on the performance of Lung Segmentation, Lung Segmentation is very crucial part of CADE and CADx systems for lung cancer. Lung Segmentation in Image Processing, is the extraction of lung region from the image. The output of segmented lung image is usually given in binary mask (only black and white image). We consider black pixels as pixels with '0' gray-level value and white pixels as pixels with '1' gray-level value. When the binary mask of the segmented image is element-wise multiplied with the original image, we get the segmented object without background details. Generally, Lung Segmentation methods are categorized into four categories: Thresholding based, Deformable Boundary Models, Shape Models and Edge Models.

A. Thresholding based Lung Segmentation

Image thresholding [2] can be used for image segmentation. The main objective of image segmentation is to separate the object from the background. If the intensity of the object is comparatively higher than that of background, then the image thresholding is performed as:

$$J(x, y) = \begin{cases} 1, & \text{if } I(x, y) \geq Th \\ 0, & \text{if } I(x, y) < Th \end{cases} \quad (1)$$

where $I(x, y)$ is the image to be segmented, $J(x, y)$ is the segmented image and Th is the threshold value.

In thorax computed tomography (CT) image, the patient's body is lighter intensity than that of the background (surrounding air space). So the body can be easily segmented by using the above formula. In case of object with darker intensity compare to that of background, then the image thresholding is performed as:

$$J(x, y) = \begin{cases} 1, & \text{if } I(x, y) \leq Th \\ 0, & \text{if } I(x, y) > Th \end{cases} \quad (2)$$

The segmented image is a binary image in which the object is represented by white pixels and the background by black pixels. The above formula can be used in segmentation of lung which is darker intensity from the surrounding body.

Methods for selecting Threshold (Th) value [3]:

1) *P-tile Method:* This method finds the percentage of area of object occupied (p %) in the image. The threshold value is obtained at (100-p) % of pixel count from the histogram of the image in case of dark background. The threshold value, in case of light background, is obtained at p % of pixel count from the histogram of the image.

2) *Mode Method:* Regions with uniform intensity with distinct objects and background, show strong peaks and deep valleys in image histogram. The threshold value can be chosen as the gray level at the point of the lowest valley. In case of flat valley, the middle gray level value of the valley is chosen as the threshold value.

3) *Otsu's Method:* In this method, the threshold value is selected at minimum intra-class variances. Minimization of intra-class variance is same as maximizing inter-class variance. The inter-class variance is given by:

$$\sigma_B^2(t) = q_b(t)[1 - q_b(t)][\mu_b(t) - \mu_o(t)]^2 \quad (3)$$

Such that $\sigma^2 = \sigma_w^2(t) + \sigma_B^2(t)$ where $q_b(t) = \sum_{i=0}^{t-1} P(i)$ and $q_o(t) = \sum_{i=t}^{L-1} P(i)$ are the probability of getting a pixel as background and the probability of getting a pixel as object respectively; $P(i)$ is the probability of a pixel with gray value 'i';

$\mu_b(t) = \frac{1}{q_b(t)} \sum_{i=0}^{t-1} iP(i)$ and $\mu_o(t) = \frac{1}{q_o(t)} \sum_{i=t}^{L-1} iP(i)$ are the means of all background pixels and the mean

of all object pixels respectively; $\sigma_w^2(t)$, $\sigma_B^2(t)$ and σ^2 are intra-class, inter-class and total variances.

4) *Optimal Thresholding Method:* Assume that the distribution of gray level values in both object and background on the image, follow a Gaussian distribution. Then, the probability of a pixel value is given by:

$$P(i) = P(\text{background})p(i | \text{background}) + P(\text{object})p(i | \text{object}) \quad (4)$$

$$P(i) = P_b \frac{1}{\sqrt{2\pi}\sigma_b} e^{-\frac{(i-\mu_b)^2}{2\sigma_b^2}} + P_o \frac{1}{\sqrt{2\pi}\sigma_o} e^{-\frac{(i-\mu_o)^2}{2\sigma_o^2}} \quad (5)$$

$$P(i) = P_b p_b(i) + P_o p_o(i) \quad (6)$$

where P_b, P_o : the a-priori probabilities of background and object pixels; p_b, p_o : probability distributions of background and object pixels; μ_b, μ_o : the means of the distributions; σ_b, σ_o : the standard deviations of the distributions.

The error of classifying an object pixel as background is given by:

$$E_o(T) = \int_{-\infty}^T p_o(i) di \quad (7)$$

The error of classifying a background pixel as object is given by:

$$E_b(T) = \int_T^{\infty} p_b(i) di \quad (8)$$

The overall probability of error is given by:

$$E(T) = P_o E_o(T) + P_b E_b(T) \quad (9)$$

After minimizing $E(T)$, we get the threshold value as:

$$Th = \frac{\mu_b + \mu_o}{2} + \frac{\sigma^2}{\mu_b + \mu_o} \ln\left(\frac{P_o}{P_b}\right) \quad [\text{Taking } \sigma_b = \sigma_o = \sigma] \quad (10)$$

Multi-level Thresholding:

We have already discussed about thresholding with a single threshold value. This is limited to object having bright or dark intensity compare to the background. In case the object's intensity lies between one or more specific range(s), then the object can be segmented by using multi-level thresholding [2]. It is given by union of all thresholded regions.

$$R[x, y, I, T_{low}, T_{high}] = \begin{cases} 1, & \text{if } T_{low} \leq I(x, y) \leq T_{high} \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

$$J(x, y) = \bigcup_{i=1}^n R[x, y, I, L(i), H(i)] \quad (12)$$

Local Adaptive Thresholding:

Local adaptive thresholding [2] selects threshold value of each pixel based on the range of gray-level values of neighboring pixels on a fixed sized sliding window.

$$J(x, y) = \begin{cases} 1, & \text{if } I(x, y) \geq T(x, y) \\ 0, & \text{if } I(x, y) < T(x, y) \end{cases} \quad (13)$$

where $T(x, y)$ is the local threshold value of pixel window

$$W_d(x, y) = \left\{ I(i, j) \left| \begin{array}{l} i = x - d, \dots, x, \dots, x + d \\ j = y - d, \dots, y, \dots, y + d \end{array} \right. \right\} \quad (14)$$

where $(2d + 1) \times (2d + 1)$ is the size of the window.

Morphological Filtering:

Morphological filtering [4] is usually used as post-processing step of image segmentation. It filters segmentation errors like improper segmentation due to luminance, non-uniform intensity distribution, similar intensity of object with background, etc. Some of the common morphological operations are dilation, erosion, opening and closing.

1) *Dilation operation:* Dilation operation is applied when the segmented object misses some part of its object region. It enlarges the region of segmented object. It increases sensitivity but decreases specificity. Mathematically, dilation operation can be defined as:

$$(f \oplus s)(x, y) = \bigvee_{i=-d}^d \bigvee_{j=-d}^d f(x+i, y+j) \wedge s(i+d, j+d) \quad (15)$$

where $f(x, y)$ is the pixel of the image at (x, y) , $s(x, y)$ is the pixel of structuring element at (x, y) and $(2d + 1) \times (2d + 1)$ is the size of structuring element.

2) *Erosion operation:* Erosion operation is applied when the segmented object includes some part of background. It shrinks some part of segmented object. It increases specificity but decreases sensitivity. Mathematically, erosion operation can be defined as:

$$(f \ominus s)(x, y) = \bigwedge_{i=-d}^d \bigwedge_{j=-d}^d f(x+i, y+j) \vee \neg s(i+d, j+d) \quad (16)$$

where $f(x, y)$ is the pixel of the image at (x, y) , $s(x, y)$ is the pixel of structuring element at (x, y) and $(2d + 1) \times (2d + 1)$ is the size of structuring element.

3) *Opening operation:* Opening operation is a combination of erosion operation followed by dilation operation. It is like erosion operation which removes some of bright background pixels but it is less destructive compared to erosion. It improves sensitivity compare to that of erosion operation. Mathematically, it is defined as:

$$(f \circ s) = (f \ominus s) \oplus s \quad (17)$$

4) *Closing operation:* Closing operation is a combination of dilation operation followed by erosion operation. It is like dilation operation which enlarges the region of segmented object but it is less destructive compared to dilation. It improves specificity compared with that of dilation operation. Mathematically, it is defined as:

$$(f \bullet s) = (f \oplus s) \ominus s \quad (18)$$

B. Deformable Boundary Model based Lung Segmentation

In this category of lung segmentation, the boundary of lung is identified by evolving a specific internal and external guiding forces to fit the shape of the lung. Snake algorithm and Level Sets are the common methods used in Deformable Boundary Model.

1) *Snake Algorithm:* Snake algorithm [5] is initiated by giving manual seed points arranged roughly in an elliptical shape. The seed points are deformed iteratively by choosing neighbouring pixels with minimal energy. The energy of neighbouring pixel is calculated as:

$$E_{snake}(v) = E_{internal}(v) + E_{external}(v) \quad (19)$$

$$E_{internal}(v) = E_{continuity}(v) + E_{curvature}(v) \quad (20)$$

$$E_{external}(v) = E_{image}(v) + E_{constraint}(v) \quad (21)$$

The energy of a pixel E_{snake} is the combination of internal energy $E_{internal}$ and external energy $E_{external}$. The internal energy is calculated as:

$$E_{internal}(v) = \frac{1}{2} \left(\alpha(s) \left\| \frac{dv}{ds}(s) \right\|^2 + \beta(s) \left\| \frac{d^2v}{ds^2}(s) \right\|^2 \right) \quad (22)$$

where $\alpha(s)$ and $\beta(s)$ are controlling parameters (weights) of energy of continuity $E_{continuity}$ and energy of curvature $E_{curvature}$ respectively. The external energy is the combination of energy of image E_{image} and energy of constraint $E_{constraint}$. The energy of image is calculated as:

$$E_{image}(v) = w_{line} E_{line}(v) + w_{edge} E_{edge}(v) + w_{term} E_{term}(v) \quad (23)$$

where w_{line} , w_{edge} and w_{term} are the weights of energies due to line, edge and termination on image respectively.

$$E_{line}(v) = I(v) \quad (24)$$

$$E_{edge}(v) = -\|\nabla I(v)\|^2 \quad (25)$$

$$E_{term}(v) = \frac{D_{yy} D_x^2 - 2D_{xy} D_x D_y + D_{xx} D_y^2}{(1 + D_x^2 + D_y^2)^{3/2}} \quad (26)$$

where $I(v)$ is the gray-level value at pixel $v = (x, y)$ on the image I ; $D_x = \frac{\partial v}{\partial x}$, $D_y = \frac{\partial v}{\partial y}$, $D_{xx} = \frac{\partial^2 v}{\partial x^2}$,

$$D_{xy} = \frac{\partial^2 v}{\partial x \partial y} \text{ and } D_{yy} = \frac{\partial^2 v}{\partial y^2}.$$

The energy of constraint $E_{constraint}$ is the energy manually specified to guide the segmentation. It depends on the application and image used to perform segmentation.

2) *Level Sets*: Level Set [6] is a set of all elements (x_1, x_2, \dots, x_d) on domain of a real function f which have same images c .

$$L_c(f) = \{(x_1, x_2, \dots, x_d) \mid f(x_1, x_2, \dots, x_d) = c\} \quad (27)$$

In image processing, Level Set (LS) can be used as image segmentation technique. It extracts all pixels having same gray-level values and label as level c .

$$J(x, y) = \begin{cases} c, & \text{if } I(x, y) = c \\ 0, & \text{otherwise} \end{cases} \quad (28)$$

The segmentation of the image is performed by choosing object boundary among those level sets L_c .

C. Shape Model based Lung Segmentation

In this category of lung segmentation, the shape of lung is modelled and matched the lung on the image to be segmented. Initially, landmark points are detected and construct a shape model of the object. The landmark points are then matched with the landmark points detected on the image to be segmented. There are two methods: active shape model and active appearance model.

1) *Active Shape Model*: Active Shape Model (ASM) [7] makes a prior model of landmark points of the object and finds the best match position of landmark points on the another image which is going to perform segmentation on it. If all the landmark points appropriately fit on the image, then the object is segmented using the landmark points as boundary of the object on the image. There are different approaches to find landmark points. Some of the common methods are edge detection, active contours, histogram of oriented gradients (HoG), scale invariant feature transform (SIFT), speeded up robust features (SURF), etc. After feature detection, principal component analysis (PCA) is usually applied in order to reduce number of feature points and to select principal feature points.

After landmark point detection, landmark points form edge lines to reconstruct an approximate shape of the object. Then, we extract gray-level profile of neighbouring pixels for each landmark point in different multi-resolution scale of the image. Finally, we construct the shape model of the object. During image segmentation, the landmark points extracted in the shape model is used to search and match with the landmark points on the image to be segmented. There are different searching approaches on detected landmark points. The gray-level profile extracted in the shape model can be used in searching landmark points corresponding to them. Finally, we find matching score. If the matching score is above a predefined threshold value, then the object can be segmented by using the landmark points as the boundary of the object.

2) *Active Appearance Model*: Active Appearance Model (AAM) [8] is an improved version of Active Shape Model (ASM). It includes both shape features as well as appearance features (esp. gradient and texture). The procedure to construct Active Appearance Model starts similarly with Active Shape Model, detection of landmark points. Edge detection, blob detection, extreme points – corners and line detection are some of commonly used for landmark point detection. For higher accuracy, this can be done manually by hand. After landmark point detection, principal component analysis (PCA) is applied to select principal feature points. Then, the feature points are registered to the image to be segmented. By using similarity measure, the matching score of the detected landmark points (including appearance feature) is evaluated. If the matching score is above a predefined threshold value, then the object is said to have detected and hence the segmentation is performed using the landmark points.

D. Edge Model based Lung Segmentation

In this category of lung segmentation, edge detection [9] is used to segment lung on the image. Edge detection methods are grouped into two categories: spatial edge detection and edge detection on transform domain. Some of the spatial edge detection methods are Robert, Prewitt, Sobel, Laplacian and Canny Edge Detection.

1) *Robert Edge Detection*: Robert edge detection performs simple and fast detection of edge feature from an image. It uses a pair of 2x2 convolution masks as follows:

$$G_x = \begin{bmatrix} +1 & 0 \\ 0 & -1 \end{bmatrix} \text{ and } G_y = \begin{bmatrix} 0 & +1 \\ -1 & 0 \end{bmatrix} \quad (29)$$

These convolution masks perform convolution with the image.

$$g_x = I \otimes G_x \quad (30)$$

$$g_y = I \otimes G_y \quad (31)$$

After applying convolution with the convolution mask, the approximate magnitude is calculated and then thresholded using a fixed threshold value T to give the edges of the image.

$$M(x, y) = \sqrt{g_x^2(x, y) + g_y^2(x, y)} \quad (32)$$

$$J(x, y) = \begin{cases} 1, & \text{if } M(x, y) \geq T \\ 0, & \text{otherwise} \end{cases} \quad (33)$$

where $J(x, y)$ is the image containing edges as set of pixels with pixel value 1.

2) *Prewitt Edge Detection*: Prewitt edge detection uses 3x3 convolution masks to detect horizontal and vertical edges on the image and finally combined to give complete edges of the image. The convolution masks of Prewitt edge detection are:

$$G_h = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ +1 & +1 & +1 \end{bmatrix} \text{ and } G_v = \begin{bmatrix} -1 & 0 & +1 \\ -1 & 0 & +1 \\ -1 & 0 & +1 \end{bmatrix} \quad (34)$$

$$g_h = I \otimes G_h \quad (35)$$

$$g_v = I \otimes G_v \quad (36)$$

After applying convolution with the convolution mask, the horizontal and vertical edges are combined and then thresholded using a fixed threshold value T to give the edges of the image.

$$M(x, y) = \max(g_h, g_v) \quad (37)$$

$$J(x, y) = \begin{cases} 1, & \text{if } M(x, y) \geq T \\ 0, & \text{otherwise} \end{cases} \quad (38)$$

3) *Sobel Edge Detection*: Sobel edge detection is a simple and improved version of Prewitt edge detection. It also uses 3x3 convolution masks to detect horizontal and vertical edges.

$$G_h = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} \text{ and } G_v = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} \quad (39)$$

$$g_h = I \otimes G_h \quad (40)$$

$$g_v = I \otimes G_v \quad (41)$$

After applying convolution with the convolution mask, the horizontal and vertical edges are combined and then thresholded using a fixed threshold value T to give the edges of the image.

$$M(x, y) = \max(g_h, g_v) \quad (42)$$

$$J(x, y) = \begin{cases} 1, & \text{if } M(x, y) \geq T \\ 0, & \text{otherwise} \end{cases} \quad (43)$$

4) *Laplacian Edge Detection*: Laplacian of an image is the combination of second order partial derivatives along x-axis and y-axis. It is given by:

$$\nabla^2 I = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \quad (44)$$

Laplacian edge detection can also be performed by using 3x3 convolution mask. There are two different convolution masks of Laplacian edge detection:

$$G = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} \text{ or } G = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} \quad (45)$$

$$g = I \otimes G \quad (46)$$

$$J(x, y) = \begin{cases} 1, & \text{if } g(x, y) \geq T \\ 0, & \text{otherwise} \end{cases} \quad (47)$$

After applying convolution with the convolution mask, the edges of the image are detected by thresholding with a fixed threshold value T .

5) *Canny Edge Detection*: Unlike other edge detection methods, Canny edge detection consists of five steps. The five steps of Canny edge detection are as follows:

- Apply Gaussian smoothing to the image.

$$G_\sigma = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \quad (48)$$

$$g = G_\sigma \otimes I \quad (49)$$

where G_σ is the Gaussian kernel, I is the image and g is the smoothed image.

- Find the gradients of intensity of the image.

$$D_x = \frac{\partial I}{\partial x}, D_y = \frac{\partial I}{\partial y} \quad (50)$$

$$M(x, y) = \sqrt{D_x^2(x, y) + D_y^2(x, y)} \quad (51)$$

$$\theta(x, y) = \tan^{-1}\left(\frac{D_y(x, y)}{D_x(x, y)}\right) \quad (52)$$

where D_x, D_y are first order partial derivatives of the image intensity I w.r.t. x and y respectively;

$M(x, y)$ is the magnitude of gradient at pixel (x, y) ; $\theta(x, y)$ is the orientation of gradient at pixel (x, y) .

- Apply non-maximal suppression.

Apply thresholding to the magnitude of gradient using a suitable threshold value T .

$$M_T(x, y) = \begin{cases} 1, & \text{if } M(x, y) \geq T \\ 0, & \text{otherwise} \end{cases} \quad (53)$$

Discard those edge points having low gradient magnitude of neighboring pixels along gradient direction $\theta(x, y)$.

- Apply double thresholding to detect weak and strong edges.

$$L(x, y) = \begin{cases} 1, & \text{if } I(x, y) \times M_T(x, y) \geq T_1 \\ 0.5, & \text{if } T_1 \geq I(x, y) \times M_T(x, y) \geq T_2 \\ 0, & \text{otherwise} \end{cases} \quad (54)$$

where T_1, T_2 are two threshold values (provided $T_1 > T_2$). Here, the strong edge point is labelled as 1 and the weak edge point as 0.5.

- Link all strong edge points by tracking nearest weak or strong edge points.

Edge Detection in Transform domain – Wavelet based:

Edges on image are assumed to be high frequency components of 2D signal (image). The high frequency components are extracted by using wavelet decomposition. Wavelet transform [10] of one dimensional signal $x(t)$ is given by:

$$X(\tau, s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x(t) \psi^* \left(\frac{t - \tau}{s} \right) dt \quad (55)$$

where $\psi^*(t)$ is the complex conjugate of continuous wavelet function $\psi(t)$; s is the scaling factor and τ is the time. In case of two dimensional signal, wavelet transform can be performed as follows:

$$F(u, v, s_1, s_2) = \frac{1}{\sqrt{|s_1||s_2|}} \iint_{x, y} f(x, y) \psi^* \left(\frac{x - u}{s_1} \right) \psi^* \left(\frac{y - v}{s_2} \right) dx dy \quad (56)$$

For discrete two dimensional signal (image), wavelet transform can be performed as follows:

$$F(u, v, s_1, s_2) = \frac{1}{\sqrt{|s_1||s_2|}} \sum_x \sum_y f(x, y) \Psi^* \left(\frac{x - u}{s_1} \right) \Psi^* \left(\frac{y - v}{s_2} \right) \quad (57)$$

where $\Psi^*(t)$ is the complex conjugate of discrete wavelet function $\Psi(t)$; s_1 and s_2 are two scaling factors along x and y directions respectively.

After wavelet transform, the image is further thresholded using a suitable fixed threshold value and the pixels above the threshold value are considered as edge pixels.

III. RESEARCH ON LUNG SEGMENTATION

Hu et al. [11] used iterative threshold to extract initial lung region. A 3D Connected Component Labelling is applied to identify lung voxels from other voxels with similar intensity. From the identified lung voxels, the trachea and bronchi are removed by using a morphological operation with a unit radius kernel. Then, left and right lungs are further separated by detecting the anterior and posterior junctions of the lung. A series of morphological smoothing operations are applied to smooth the segmentation boundary and to remove small airways and vessels inside the lung region. It used 24 datasets from 8 patients and achieved less Root Mean Square Distance error of 0.54 mm (0.8 pixel). Ukil and Reinhardt [12] extended the segmentation method used by Hu et al. [11]. Airway Segmentation of lung is performed and airway anatomical labelling is applied to the segmented lung airways. Vessel Segmentation is performed to find Vessel Distance Map which is used in Watershed Transform with the original image to mark vessels. Fissure Segmentation is performed using the initial segmentation and vessel marks. Finally the fissure refinement is done using Oblique Fissure Segmentation and Horizontal Fissure Segmentation.

Van Rikxoort [13] used Region Growing Algorithm for lung segmentation. A supervised filter is used for pulmonary fissure extraction and voxel classification for lung lobes extraction. Cumulative Position inside the object, Eigenvalues of Hessian Matrix and gray-value information on different scales are used as features for voxel classification. The k -nearest neighbor classifier is used to classify voxels. This method performed segmentation of pulmonary segments with 77% accuracy which is comparable to both inter-observer and intra-observer accuracy (74% and 80% respectively). Ross et al. [14] proposed similar method used by Hu et al. [11] but Otsu's method [15] is used to find threshold value of lung segmentation from High Resolution Computed Tomography (HRCT). They also introduced 16-bits Label Map Representation which contains information about regions and their types. They further extended to interactive lobe segmentation in which user can simply scroll through the slices of HRCT and can click on points along the three major fissures: left oblique, right oblique and right horizontal, interactively.

Yim et al. [16] extracted lung using 3D Inverse Seeded Region Growing (iSRG) algorithm from the thresholded image and then a 3D Connected Component Labeling is applied to remove voxels of surrounding air. They also included airway extraction by using 3D region growing algorithm with automatic seed point selection. The extracted airways are, then, removed from the segmented lungs. They used dataset from 10 subjects and achieved with less Root Mean Square Distance error of 1.2 pixel. Armato et al. [17, 18] used automatic intensity based thresholding to segment thorax from background and then lungs from the thorax. They used a rolling ball filter to smooth the boundary of lungs and to avoid the loss of juxtapleural nodules. Pu et al. [19] extracted initial lung region by selecting a threshold value automatically as described by Armato et al. [17] and then used a geometric approach using marching cubes algorithm to model the lung volume. A Laplacian smoothing is applied to depress non-fissure structures and hence enhanced pulmonary fissures by smoothing the surfaces of lung fissures.

Pu et al. [20] also introduced a geometric analysis of lung border known as Adaptive Border Marching (ABM) algorithm to minimize the problem of over-segmentation and the segmentation error due to juxtapleural nodules. They concluded ABM is more robust, more efficient and simpler to implement. By analyzing with deep observation using 20 datasets, it found 0.43% of average over-segmentation ratio and 1.63% of under-segmentation ratio. Improvement of both accuracy and time complexity have also been shown. Gao et al. [21] proposed an optimal thresholding based lung segmentation method. By using region growing algorithm, large pulmonary airways are removed and then smoothed by using isotropic diffusion. Further, the left and right lungs are separated by detecting anterior and posterior junctions. Finally a morphological rolling-ball smoothing is applied to the lung boundary along the mediastinum and lung wall. They

used eight CT scans of four patients from a screening program for early detection of lung cancer and found 0.9946 as dice similarity coefficient.

Wei et al. [22] introduced Lung Lobe Segmentation in High-Resolution Isotropic CT images mainly used for surgical planning of treating lung cancer. They used Adaptive Fissure Sweeping to find the fissure regions and Wavelet Transform to identify the fissure location and curvature within the region. Under strict evaluation, it yielded an accuracy of 76.7% to 94.8%. Ye et al. [23] used a 3D adaptive fuzzy thresholding method followed by 1D Gaussian smoothing [24], to extract lung region from thoracic CT images. Itai et al. [25] used 2D parametric deformable model, SNAKES algorithm, to segment lung region from CT image without considering any manual operations. They further added voxel classification in order to detect the abnormal areas of lung cancer. They used 9 datasets (3 normal and 6 abnormal cases) and found true positive fraction of 0.81, false positive fraction of 0.2 and false negative fraction of 0.2 under the receiver operating characteristic (ROC) analysis.

Silveira et al. [26] proposed a new geometric based level sets technique to segment lungs from CT images. Initially, gray-level image thresholding is applied and then the edges of the thresholded image are detected. Then, the edge points are organized into strokes and classified as valid or invalid. A confidence degree (weight) for each valid strokes is calculated based on the distance between the stroke points, the curvature and stroke size. Through the evolution process, the confidence degree of strokes are updated and finally the lung boundary is formed and the lungs are segmented by using the lung boundary. Annangi et al. [27] extracted lung region from radiograph images using deformable level-set model in which a prior shape model [28] is used to initiate the process and region-based data statistics [29] is used to find the guiding energy to extract the lung boundary across the shading effects due to presence of rib cage and clavicle. They used 1130 clinical radiograph images and found 0.88 as dice similarity coefficient.

Shi et al. [30] also extracted lung region from radiograph images using a new deformable shape model. The initial seed points are detected by using a modified scale invariant feature transform (SIFT) local descriptor, which is more distinctive than the general intensity and gradient features. Using population-based and patient-specific shape statistics as constraints to the deformable contour, the lung region is segmented. They used 247 radiograph images and achieved 0.92 as overlap measure and 1.78 as mean absolute surface distance. Van Ginneken et al. [31] compared optimized active shape models [24], active appearance model and a multi-resolution pixel classification method that employs a multi-scale filter bank of Gaussian derivative and k-nearest-neighbors classifier. Using 247 chest radiographs of the publicly available JSRT database, they found that the multi-resolution pixel classification gave the best result among all the three supervised segmentation methods. Hardie et al. [32] used the lung segmentation using optimized active shape model of Van Ginneken et al. [33] to identify pulmonary nodules of lung cancer from the segmented lungs.

Sun et al. [34] introduced a novel 3D robust active shape model (RASM) to segment lungs from CT image. First, the rib cage of chest is detected and the mean value of the detected rib cage is taken as the initial position of RASM. Second, a global optimal surface finding method [35] is used to identify lungs from the CT image, and then the left and right lungs are segmented separately. Using 30 CT scans, the method achieved 0.975 dice similarity coefficient and 0.84 mm as mean absolute surface distance error. Besbes and Paragios [36] introduced a graph-based shape model with image cues based on boosted features. The normalized Euclidean distance is used to find the distance feature between the pairs of control points and then graph searching method is applied on the landmark points to construct the shape model. The method implemented unsupervised clustering methods to classify the landmarks of image points using boosted classifiers. They used 247 radiograph images and achieved 0.9474 overlap measure and 1.39 pixel as mean absolute surface distance error.

Sluimer et al. [37, 38] used segmentation-by-registration scheme to segment lungs which contain dense pathologies. The chest image is registered to fix on a standard geometric form by applying a series of geometric transformations. The transformed image is then masked by a suitable mask from different 15 registered normal lungs. Voxel classification is applied to refine the segmentation boundary. The algorithm is tested using 26 CT scans and achieved 0.8165 as overlap measure and 1.48 mm as mean absolute surface distance error. Sofka et al. [39] proposed a multi-stage learning-based approach to extract lung region from CT image. The location of carina of the trachea is used to initiate the landmark point detection. The detected landmark points are used to align the shape of the lungs and then refined through boundary detection. They used 260 CT scans and achieved 1.95 as symmetrical point-to-mesh comparison error.

Kockelkorn et al. [40] introduced an interactive system for lung segmentation which contain high-density pathology. In this method, the chest CT image is divided into small Volume of Interests (VOIs) and then textural features of each VOI are extracted. The extracted textural features are then trained using texture based statistical k-nearest neighbor classifier. They used 22 CT scans and achieved 0.96 as overlap measure and 1.68 mm as mean absolute surface distance error. Hua et al. [41] used a graph-based searching approach to segment lungs from CT image. Using intensity based thresholding, the initial lung region is extracted. The image feature: intensity, gradient, boundary smoothness and the rib information are extracted. The extracted features are then trained using k-nearest neighbor classifier. Finally, the lung boundary is refined using graph search algorithm. Using 15 CT scans, the method achieved 13.3 pixel as Hausdorff distance, 0.986 as sensitivity and 0.995 as specificity.

El-Baz et al. [42-44] introduced iterative Markov-Gibbs-Random-Field- (MGRF-) based segmentation to segment lung region from CT image. First, a linear combination of discrete Gaussian (LCDG) model with positive and negative components [45, 46] are applied. Second, voxel-classification using Bayesian Maximum a Posteriori (MAP) classifier is used for initial segmentation. Then Iterative Conditional Model (ICM) is used to refine the lung segmentation. They further extended their work by applying on different scale space [47, 48]. Finally the segmentation of different scales were

fused using Bayesian fusion approach. Ali et al. [49] used graph-cut segmentation algorithm on iterative MGRF-based model [42-44]. First, image signal labelling and modelling is performed. Second, identification of spatial interaction between the neighboring pixels is done with Potts model parameter. Finally, the energy is minimized using graph-cut method and hence the lung region is extracted. Campadelli et al. [50] detected edges from chest radiograph images using first order derivation of Gaussian filter taken at four different orientations and then Laplacian of Gaussian (LoG) at three different scales, is applied to track edges of lung boundary. They used 487 radiograph images and achieved an accuracy of 94.37%.

Mendonca et al. [51] used spatial edge detector to segment lung region from chest radiograph image. The method started by identifying rectangular regions of interest (ROIs) of both left and right lungs, and then accurate segmentation of lung boundary is performed on each rectangular ROIs. The method performed efficiently by detecting mediastinal pixels, costal edges, top edges and bottom edges, by eliminating outlying edges, and combination of remaining edges. They used 47 radiograph images and achieved 0.9225 as sensitivity and 0.968 as positive predictive value. Korfiatis et al. [52] extracted lung region from CT image by using Wavelet Transform. The high spatial frequency component of the image contains the edge features of the image. The edges are extracted by using optimal thresholding [53] on high frequency component of the image. Further, a 3D morphological processing is applied to refine the final segmentation.

Soliman et al. [54] developed Joint Markov-Gibbs based lung segmentation approach from CT image. They also proposed a new framework to generate 3D realistic synthetic phantoms which can be used to evaluate the performance of any lung segmentation methods. The segmentation framework was initiated by Gaussian filtering of the original CT data in different scale space and the marginal intensity was estimated using Linear Combination of Discrete Gaussians (LCDG) approach to get an initial map. The initial maps are iteratively refined and the final map is obtained by fusing all scale space together to get the segmented lung region. Qi et al. [55] performed lung lobe segmentation and pulmonary fissure detection from chest CT image. Initially, using sagittal adaptive fissure scanning, the potential fissure regions are localized. Then, a Hessian matrix based line enhancement filter is applied in coronal slice followed by shortest path searching technique by means of Uniform Cost Search. Finally, extraction of fissure surface is performed using implicit surface fitting based on Radial Basis Functions to segment the five lung lobes. The method used 14 datasets and achieved lesser root mean square errors of 2.46 mm for right oblique fissure, 3.13 mm for right horizontal fissure and 3.25 mm for left oblique fissure.

Hosseini-Asl et al. [56] used a new Non-negative Matrix Factorization (NMF) approach to segment lung region from CT image. The method has the ability to handle the inhomogeneity in the lung region, one of the research challenges of lung segmentation, caused by arteries, veins, bronchi and pathological tissues. Using fourteen CT scans, the method outperformed other lung segmentation techniques based on the dice similarity coefficient. Soliman et al. [57] extracted lung region using a novel 3D joint Markov-Gibbs Random Field (MGRF-) model with integrated three features: the first order visual appearance model, the second order spatial interaction model and a shape prior model of the lung. Using 20 datasets with different types of pathologies, the method achieved high accuracy compared to other lung segmentation methods.

Zhou et al. [58] introduced a robust atlas-based active volume model with a sparse shape composition prior to segment compromised right lung from CT image. The method achieved mean dice similarity coefficient of (0.72, 0.81) with 95% CI, mean accuracy of (0.97, 0.98) with 95% CI, and mean relative error of (0.46, 0.74) with 95% CI. Sun et al. [59] proposed an improved active shape model to segment abnormal lung regions from CT image. The method initiated by identifying outlier marker point by distance and then applied different search functions to both the abnormal and normal markers. The method was tested using 40 pathological lungs which contain mass, the overlap rate with the gold standard is 93.6%. Wang et al. [60] proposed Higher-order Singular Value Decomposition (HOSVD)-based Three-dimensional (3D) Active Appearance Model (AAM) to segment lung region with high-density pathologies. The method used HOSVD before applying the AAM which convert 3D CT data into higher-dimensional tensor space. The method improved processing speed and reduced the memory consumption during segmentation process. Using 310 diseased lungs, the method achieved average dice similarity coefficient of 97.0 %, a mean absolute surface distance error of 1.0403 mm, a mean border positioning error of 0.9187 pixel and a Hausdorff distance of 20.4064, respectively.

IV. RESEARCH CHALLENGES AND FUTURE PROSPECTS

Lung Segmentation is the most crucial and first processing step of any computer assisted diagnosis (CADe or CADx) system for lung cancer. The challenges of the segmentation of lung region are:

- Inhomogeneity in lung region.
- Similar density with other pulmonary structures.
- Different scanners and scanning protocols.

The existing methods of lung segmentation require further improvement in terms of:

- Accuracy including sensitivity and specificity.
- Processing speed.
- Automation level.
- Reliability and Robustness.
- Installation and maintenance cost.

V. CONCLUSION

In this paper, the methods of lung segmentation for detection and diagnosis of lung cancer are discussed in detail under four categories namely: thresholding based, deformable boundary model based, shape model based and edge model based. The recent research methods on lung segmentation are also presented in this paper. Finally, the research challenges and future prospects of lung segmentation are discussed.

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