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Segmentation of lung from CT using various active contour models

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ABSTRACT

The aim of the paper is to develop a region based active contour model using variational level set function for segmentation of lung. Ultimately, segmentation of parenchyma is essential for accurate diagnosis of various lung diseases. Among many imaging modalities, Computed Tomography (CT) is a pioneer to most image analysis applications. This work proposes a powerful technique named Selective Binary and Gaussian filtering-new Signed Pressure Force (SBGF-new SPF) function for segmentation of CT lung images. This process detects the external boundary of the lung and effectively stops the contour even at blurry boundaries. The proposed algorithm was compared with four different active contour models. Comparative experiments demonstrate the advantage of proposed method in terms of computation time and accurate segmented lung.

1. Introduction

Lung cancer is one of the deadliest cancers of all other cancers. Early detection and diagnosis is the only way to minimize high mortality rate. In medical imaging, Computer Aided Diagnosis (CAD) system works as the main component in research streams [1].

Segmentation of parenchyma from CT images only paves way to identify the nodule easier to detect lung disease. The objective of this stage is to eliminate the background (mediastinum, thoracic wall, heart, liver, fat, muscles etc) from the lung. Separation of parenchyma from the CT images can be performed using different methods such as region growing [2,3], watershed segmentation [4], fuzzy logic [5], intensity based thresholding [6], graph search algorithm [7], etc. However, there are several limitations like over computation time, less accuracy, high segmentation error and so on. Morphological operations [8,9] are also used for lung segmentation. Yet, the boundary of the images cannot be preserved. To preserve the edges with less computation time the proposed methodology uses Active Contour Model (ACM). ACM can be used to track the dynamic objects. ACM looks for any shape in the image that is smooth and forms a closed contour. Active contour model can also be named as deformable model, snakes, balloon. There exist two types of ACM; edge based and region based.

Edge based model produces small variation in segmentation due to image gradients. These image gradients are denoted by edge indicator function. If weak boundary exists, leakage problem arises too [10]. Presence of noise in the boundary and non-uniform edges cannot be tackled in edge based approach.

Region based do not use image gradient rather uses statistical information for controlling the contour inside and outside the object boundary throughout the evolution. Region based models are less sensitive to weak edges, noise, inhomogeneity, poor contrast etc. They do not produce boundary leakage problem. It is observed that region based ACM hinders the effect of problem that arises in edge based model.

Basically, for a contour to perform its function it requires two forces. They are internal force and external force. Internal force comprises of elastic energy and bending energy. The elastic energy is responsible for shrinking the contour, and bending energy is responsible for bending the contour. Internal forces bend or shrink within the image domain. External force is responsible for defining the function along the boundaries. External forces are computed from image data such as line, edge and termination function.

Some of the region based models are Mumford-Shah functional model which is a Piecewise Smooth (PS) model [11], Chan Vese's (CV) Piecewise Constant (PC) model [12], and so on. The PS model handles inhomogeneity images to some extent. But complex procedure involves and increases the cost of computation. The PC model assumes all images as homogeneous. Hence this method fails to handle inhomogeneity images.

Depending upon the placement of positioning the initial contour segmentation can be categorized into local segmentation and global segmentation. If the initial contour surrounds the lung lobe to be segmented, then it is called local segmentation. If the initial contour starts anywhere in the imaging modality, and if the lung is detected automatically then it is called global segmentation.

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Lung parenchyma has nodular part present along the lung wall which is named as pleura nodule. If contour is correctly identified, then pleura nodule can be correctly detected. Technique such as region growing, watershed, morphology etc. do not identify object boundary. Hence the nodule present in the boundary cannot be identified. This is the main drawback of the above said techniques. The ACM identifies the boundary correctly and hence this is the most suitable method for pleura detection.

Distance Regularized Level Set Evolution (DRLSE), Local Binary Fitting (LBF), Local Gaussian Distribution Fitting (LGDF), Local Image Fitting (LIF) and Selective Binary and Gaussian Filtering with new Signed Pressure Force (SBGF-new SPF) function are some of the contouring models discussed in this work. The reason for choosing these models is to preserve the boundary of the lung lobe with less computation time. Comparision of various contouring models and their corresponding outputs are discussed below:

2. Different active contour models (ACM)

Level set evolution has been widely used in the image processing field especially in the background of deformable model for image segmentation. The level set function utilizes two terms such as distance regularization and energy minimizing function to force the level set to the most wanted contour location [13].

2.1. Edge based model (the distance regularized level set evolution (DRLSE) model)

DRLSE developed by [13] is an edge based contour model, uses variational LS to reduce the irregularities which occur during the evolution.

The variational level set formulation for the DRLSE model can be described as

$$\frac{\partial \phi}{\partial t} = \mu div \left(dp \left(\left| \nabla \phi \right| \right) \nabla \phi \right) + \lambda \delta_Z (\phi) div \left[g \frac{\nabla \phi}{\left| \nabla \phi \right|} \right] + \alpha g \delta_Z (\phi) \quad (1)$$

$$\delta_z = \frac{1}{\pi} \frac{\varepsilon}{\varepsilon^2 + z^2} \quad (2)$$

The first term of Eq. (1) is related to distance regularization function; second and third term denotes the external energy function. The energy indicator function 'g' is mainly used to improve the smoothness of the image in order to reduce the noise. The Gaussian kernel with standard deviation σ is used to smooth the image and reduce noise. λ, α denotes the coefficient of weighted length and weighted area. δ_Z is dirac delta function as given in Eq. (2).

Depending upon the condition of α the contour expands or shrinks. For positive α, the contour shrinks; and for negative α, the contour expands. If the initial contour is inside the lung lobe the DRLSE model segments that lung area, on the other hand when part of the initial contour are outside the lung lobe the result is not sensible. Furthermore, re-initialization is required to implement this model to acquire complete lung, which is computationally expensive.

Region based model can be categorized into local and global depending on contouring function. If the initial contour is placed surrounding the lung region, then it is said to be local. No matter where the initial contour starts, the lung automatically identifies the contour then it is said to be global.

2.2. Local region based model

2.2.1. Local binary fitting (LBF) model

The LBF model [10] was proposed to segment intensity inhomogeneity images. Assume a contour c in an image domain Ω.

The level set representation of the LBF model is given as

$$E^{LBF}(\phi, f_1, f_2) = \lambda_1 \int_{in(c)} K/(I - f_1)^2 H_x(\phi) dx + \lambda_2 \int_{out(c)} K/(I - f_2)^2 \times (1 - H_x(\phi)) dx \quad (3)$$

For a given image I, f_1, f_2 are the image fitting functions outside and inside the contour, K is the kernel function. λ_1, λ_2 are the weighted positive constants. The first term and second term in Eq. (3) denotes the LBF energy.

H_x – Heaviside function

$$H_x = \frac{1}{2} \left[1 + \frac{2}{\pi} \arctan \left(\frac{x}{\varepsilon} \right) \right] \quad (4)$$

Since this model exploits local intensity means, it fails to segment the CT medical images correctly by showing some unwanted contours. The blood vessels inside the lung cannot be identified.

2.2.2. Local gaussian distribution fitting (LGDF) model

The LGDF model [14] was a local region based active contour model. The size of each region is determined by Gaussian kernel σ. For an input image I the energy function in terms of σ, u, ϕ is given as in Eq. (5)

$$E^{LGDF} \left(\phi, u_1(x), u_2(x), \sigma_1^2(x)^2, \sigma_2^2(x)^2 \right) = B_1 + B_2 \quad (5)$$

$$B_1 = -\int \omega(x - y) \log p_{1,x}(I(y)) H(\phi(y)) dy \quad (6)$$

$$B_2 = -\int \omega(x - y) \log p_{2,x}(I(y))(1 - H(\phi(y)) dy) \quad (7)$$

The energy function is rewritten in Eq. (8) with the aid of (6), (7)

$$F \left(\phi, u_1, u_2, \sigma_1^2, \sigma_2^2 \right) = E^{LGDF} \left(\phi, u_1, u_2, \sigma_1^2, \sigma_2^2 \right) + \nu L(\phi) + \mu P(\phi) (8)$$

where ν, μ >0 are weighting constants. $L(\phi)$, $P(\phi)$ are used to regulate the level set evolution by penalizing its length and its derivative to derive a smooth contour from a SDF. The size of each region is determined by Gaussian kernel σ. When σ is small the resultant image will be sensitive to noise, whereas when σ is large oversmooth images results in.

2.2.3. Local image fitting (LIF) model

The LIF model is used to extract images with local information which is proposed by [15]. It was able to segment images with intensity inhomogeneities and eliminates the need of re-initialization. The main drawback of this model is that it is computationally expensive.

$$E^{LIF}(\phi) = \frac{1}{2} \int \left(I - I^{LIF} \right)^2 dx, x \in \Omega \quad (9)$$

This is considered by taking the discrepancy between fitting output and input image. The fitting output image is calculated by using the function given below as in Eq. (10).

$$I^{LIF} = m_1 H_x(\phi) + m_2 (1 - H_x(\phi)) \quad (10)$$

where H_x is the Heaviside function as given in Eq. (4). The experiments also show that this method does not achieve satisfying segmentation result. The CPU time is large.

2.3. Global region based model

2.3.1. Chan-Vese's piecewise constant (PC) model

PC models proposed by [12] was based on the assumption that intensities of image in each region are homogeneous. The minimized energy functional of Mumford and Shah model was further