LUNG DETECTION IN CT IMAGES BY USING IMPROVED ACTIVE CONTROL MODEL

Jyung Hyun Lee¹, Chul Ho Won², Dong Hun Kim¹, Yeon Kwan Moon¹, Eui Sung Jung¹, Sang Hyo Woo¹, Byung Seop Song³, Jin Ho Cho¹
¹Dept. of Electronic Eng., Kyungpook National University, ²Dept. of Computer Control Eng, Kyungil University, ³Dept. of Rehabilitation Science and Technology, Daegu University
33 Buho-ri Hayang-up Kyungsan-si Kyungbuk, 712-701, Republic of Korea
chulho@kiu.ac.kr

ABSTRACT
Active contour models have been extensively used to segment, match, and track objects of interest in computer vision and image processing applications, particularly for locating object boundaries. With conventional methods an object boundary can be extracted by controlling the internal energy and external energy based on energy minimization. However, this still leaves a number of problems, such as initialization and poor convergence in concave regions. In particular, a contour is unable to enter a concave region based on the stretching and bending characteristic of the internal energy. Therefore, this study proposes a method that controls the internal energy by moving the local perpendicular bisector point of each control point on the contour, and determining the object boundary by minimizing the energy relative to the external energy. Convergence at a concave region can then be effectively implemented as regards the feature of interest using the internal energy, plus several images can be detected using a multi-detection method based on the initial contour. The proposed method is compared with other conventional methods through objective validation and subjective consideration. As a result, it is anticipated that the proposed method can be efficiently applied to the detection of the pulmonary parenchyma region in medical images.

KEY WORDS
Lung Parenchyma, CT images, Active Contour Model, and Multi-detection

1. Introduction
Extracting the pulmonary parenchyma from a pulmonary image is important for the early detection of a local pulmonary function disorder and diffuse pulmonary disease, a progress trace, and medical examinations based on quantitatively measuring the pulmonary parenchyma density and identifying the density distribution curve[1,2]. There are several ways of detecting a closed contour. The first and simple method is based on thresholding, where the pulmonary parenchyma is detected by determining the proper threshold and creating a binary image using the histogram distribution. However, setting the proper threshold is difficult and a region with a similar luminance level can be simultaneously detected[3]. The use of an edge operator is also a straightforward method, however, since a closed contour can not be obtained [4], an edge tracing method is also needed to extract the pulmonary parenchyma contour after obtaining the intensity and direction information of the edge using a directional edge operator. Nonetheless, subtle noise can also be detected as a contour[5].

More recently, closed contours are detected using an active contour model considering the shape of the region of interest and image features. An active contour model detects the contour of the object of interest by minimizing the energy controlling the internal and external energy, as originally proposed by Kass et al[6]. However, this method is decisively affected by limited conditions related to the derivative possibility of the energy numerical formula and initialization. To overcome these problems, several methods have already proposed. For example, the application of dynamic programming[7] provides more stability, yet the algorithm is extremely slow, computationally complex, and time consuming. A greedy algorithm[8] can improve the stability, flexibility, and speed, but non-optimal solution is often produced without using the information obtained in the previous step. Furthermore, conventional active contour models also have a problem with concave regions, as in this case the contour of the object cannot be extracted, since the movement of the contour does not progress in a concave region.

To overcome the concave problem, the new external energy called the GVF (gradient vector flow) is proposed by Xu et al [9,10]. This energy is calculated by gradient vector diffusion of binary or gray scale edge map. However, this model is unable to detect several regions. Accordingly, this paper uses energy minimization to solve the concave problem based on controlling the internal energy moving from each control point assigned in the contour to the local perpendicular bisector. The proposed internal energy is to move the contour to concave region. Then, multiple objects can be detected in relation to the initial contour by dividing the contour based on a comparison of a minimal interval for the contour.
progressing between objects. Previously, a density distribution curve was analyzed by extracting pulmonary parenchyma from pulmonary EBT (electro beam computerized tomography) images, then several parameters were generated from this analysis for the early diagnosis of diffuse pulmonary diseases and functional disorders of the local pulmonary. Therefore, this paper investigates a variational approach for energy minimization as an initial active contour model, and analyzes the proposed method as a solution to the concave problem and for detecting multiple objects. The effectiveness of the proposed method is then confirmed in applying to pulmonary EBT images.

2. Initial Active Control Model

The original active contour model was introduced as "snakes" and derived by a variational principle from a nongeometric measure. The model starts from an energy function that includes "internal" and "external" terms that are integrated along a contour. Let the contour, \( v(s) = [x(s), y(s)] \), where \( s \in [0, 1] \) is an arbitrary parameterization. The active contour model moves through the spatial domain of an image to minimize the energy function. That is, the contour is detected by minimizing the energy function by matching the internal energy and external energy, as in Eq. (1).

\[
E_{\text{snake}} = \int_0^1 E_{\text{snake}}(v(s)) ds = \int_0^1 (E_{\text{int}}(v(s)) + E_{\text{ext}}(v(s))) ds
\]

where, \( E_{\text{int}} \) denotes the internal energy of the active contour and \( E_{\text{ext}} \) is derived from the input image as the external energy. \( E_{\text{int}} \) depends on the intrinsic character of the curve as a summation of the elastic energy and bending energy to discourage stretching and bending, as in Eq. (2).

\[
E_{\text{int}} = E_{\text{elastic}} + E_{\text{bending}} = \int_0^1 \left( \alpha \left| v_s(s) \right|^2 + \beta \left| v_{ss}(s) \right|^2 \right) ds
\]

where \( \alpha \) and \( \beta \) are the weighting parameters that control the tension and rigidity of the active contour model, respectively, and \( v_s(s) \) and \( v_{ss}(s) \) denote the first and second derivatives of \( v(s) \), respectively, with respect to \( s \). The external energy \( E_{\text{ext}} \) is also minimized based on a summation with the internal energy at the feature of interest, such as the boundary. Given a gray-level image \( I(x, y) \), viewed as a function of continuous position variables \( (x, y) \), the typical external energy is

\[
E_{\text{ext}}(x, y) = \left| \nabla I(x, y) \right|^2
\]

where \( \nabla \) is the gradient operator and minimizes the energy function relative to the internal energy using the magnitude in the edge region.

Fig. 1(b) shows the problems of the conventional active contour model as regards boundary concavity and initialization. The model has difficulty progressing in a concave region as the elastic and bending energy is depressed, plus careful conditions are required for initialization.

3. Proposed active contour model

In this paper, the new internal energy function controlled by moving the local perpendicular bisector point of each control point on the contour was proposed, and new detection algorithm for multiple objects is implemented in relation to the initial contour by minimizing the energy based on a summation of the internal energy and external energy. Fig. 2 presents a flowchart for detecting an object contour. First, median filtering is implemented for noise removal and edge strengthening, then the initial contour is generated around the region of interest. The contour then moves in the direction to minimize the summation of the internal and external energy. Control points are added or removed from the contour to maintain a regular interval between iterations in relation to the above movement. This iteration process is repeated until the number of control points no longer changes with the convergence of the contour. Multiple objects can then be detected by dividing the contour based on a comparison of a minimum interval for the contour progressing between objects.
3.1 Improved detection of concave region

As the preprocessing stage, median filtering removes the noise and strengthens the edges in a medical image. The initial contour is then generated around the object of interest, and initial control points assigned to regularly sample points on the contour. Each of the assigned control point $v_i(x_i, y_i)$ is moved for controlling the internal energy, as proposed in Eqs. (4) and (5).

$$\begin{align*}
    x_{\text{mid}} &= \frac{(x_i + x_{i+1})}{2} \\
    y_{\text{mid}} &= \frac{(y_i + y_{i+1})}{2}
\end{align*}$$

(4)

$$\begin{align*}
    (x_i') &= \left( \frac{1}{\cos \theta} \right) \times \left( \cos \theta \sin \theta \right) (x_{\text{mid}} - x_i) \\
    (y_i') &= \left( -\sin \theta \cos \theta \right) (y_{\text{mid}} - y_i)
\end{align*}$$

(5)

where $x_i, y_i$ is the x, y position of control points, $i$ means $i$th control point among several control points, $v_{\text{mid}}(x_{\text{mid}}, y_{\text{mid}})$ denotes the mid-point between two control points $v_i(x_i, y_i)$ and $v_{i+1}(x_{i+1}, y_{i+1})$, and $v_i'(x_i', y_i')$ is the point moved to the perpendicular bisector. That is, the contour is moved based on the internal energy controlled using the rotational transform in Eq. (5), and $\theta$ angle controls the scale of the internal energy.

$E_{\text{image}}$ represents the slope of the image in Eq. (6) and is led through a Sobel operator as the first differential operator in Eq. (7).

$$\nabla I_y (x, y) = I(x+1, y+1) + 2I(x+1, y) + I(x+1, y-1) - I(x, y+1) - I(x, y-1)$$

(6)

$$\nabla I_x (x, y) = I(x+1, y+1) + 2I(x, y+1) + I(x-1, y) - I(x+1, y) - I(x, y-1)$$

(7)

$\nabla I_x, \nabla I_y$ is the slope of x, y direction, respectively, $\nabla I(x_{\text{mid}}, y_{\text{mid}})$ is the sum of two slopes to represent the edge magnitude at $(x_{\text{mid}}, y_{\text{mid}})$ position. $\gamma$ for control of external energy minimizes the summation of the internal energy as the parameter controlling the energy effect related to the image luminance and background. Eq. (8) shows that the contour moves toward the direction minimizing the energy function based on the summation of the internal energy $E_{\text{int}}$ and external energy $E_{\text{ext}}$.

$$E_{\text{min}} = E_{\text{int}}(x, y) + E_{\text{ext}}(x, y)$$

(8)

In Fig 3, the control point on the contour is moved according to the internal energy controlled using the parameter angle $\theta$ of the middle points between $v_i$ and $v_{i+1}$. The movement of the assigned control points on the initial contour then approaches the direction of the region of interest based on iterations in relation to controlling the internal energy. At the edge of the object, the control points are converged using $E_{\text{min}}$ and continue to progress in a concave region.

In Fig 4, as with the total process in Fig 3, each control point moves along the local perpendicular bisector locations of the control points according to the $n$-th iteration and progresses into a concave region based on an iterative process in relation to controlling the internal energy. In the case of background, the control points on the contour continue to progress, as the internal energy is stronger than the external energy. For an edge with a strong external energy, the control points converged at the edge by energy minimization based on a summation of the internal energy and external energy.

3.2 Detection of multiple objects

Multiple objects can be simultaneously detected by dividing the contours through comparison based on a 41
minimum interval for the contours progressing between the objects. That is, as the interval for the contours progressing between the objects approaches a minimum distance, the contours are divided and converged to each object by an iterative process. However, in the case of a large interval between the objects, the contour cannot be converged to the object, as certain control points on the contours divided by the next iteration may meet again. Thus, to solve this problem, the contour continues to progress after being divided from the control point for the first minimum distance to the next control point, which is larger than a conditional distance.

Fig. 5. Flowchart for multi-object detection.

In the flowchart in Fig. 5, \( \text{dis}_{con} \) is the condition of the initial minimum distance that divides the contours progressing between the objects, while \( \text{dis}_{cp} \) is the distance between the control points on the contours, and the contour can be divided again by a control point exceeding \( 5 \times \text{dis}_{con} \). That is, \( \text{Contour}_1 \) can be divided at the control point of the initial minimum distance and \( \text{Contour}_2 \) is divided at the control point exceeding \( 5 \times \text{dis}_{con} \).

In Fig. 6, the first contour, \( \text{Contour}_1 \), is divided at the first minimum distance, where the contour for the upper position and contour for the lower position progressing between the objects approach each other. Then, the second contour, \( \text{Contour}_2 \), is divided again where the distance exceeds the condition as in Fig. 5. The iterative process is finished when the number of control points no longer changes, thereby allowing multiple objects to be simultaneously detected from the initial contour.

4. Result

Fig. 7(a) shows that the contour converged after 10 iterations in a concave region when using the proposed method, while Fig. 7(b) shows the improved result from the conventional method in Fig 1(b). In addition, Fig. 7 (c) shows the multiple objects detection is possible by using proposed method. As such, it was verified that the contour properly converged with the object of interest when using the proposed method.

Fig. 6. Movement and separation of contour among objects.

Fig. 7. (a) 10 repetitions and convergence of initial contour and (b) improved spanner image (c) 4 objects detection

The validity of the proposed method was confirmed based on a comparison of the square root average error \( E_{rms} \) and \( C_{size} \) contour size between the conventional method and the proposed method.

\[
E_{rms} = \sqrt{\frac{1}{N} \sum_{i=0}^{N-1} (r(i) - c(i))^2}
\]

(11)

\( E_{rms} \) denotes the distance error value between the control points \( r(i) \) on the reference contour and the control points
\( c(i) \) on the comparison contour, \( N \) and represents the number of control points on the comparison contour. Fig. 8 shows the reference images used to validate the detection of a concave region and multiple objects, and Fig. 8(b) shows the basic model specifically considered for a pulmonary EBT image.

Fig. 8. (a) Reference image I and (b) reference image II for validation.

Fig. 9 shows that the contour was unable to progress into a concave region and did not detect the two objects when using conventional active contour models: initial active contour model, dynamic programming, and greedy algorithm. Conversely, in Fig. 10, the contour naturally progressed into a concave region and the two contours also exactly detected the two objects when using the proposed method. In this simulation, used parameters are iteration number: 80, \( \alpha \): 0.68, \( \beta \): 0.051 for all the active contour model, and for the proposed algorithm \( \delta \): -0.9. For the GVF parameters are iteration number: 125, \( \alpha \): 0.05, \( \beta \): 0, \( \gamma \): 0.05, \( \kappa \): 0.6, and \( \mu \): 0.2.

Table 1 verifies the improved result when using the proposed method through a comparison of the \( E_{rms} \) and \( C_{size} \) in reference images I and II.

<table>
<thead>
<tr>
<th>Method</th>
<th>Measure</th>
<th>Conventional</th>
<th>Greedy</th>
<th>Dynamic</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ref. I</td>
<td>( E_{rms} )</td>
<td>3.380</td>
<td>2.924</td>
<td>3.003</td>
<td>1.456</td>
</tr>
<tr>
<td></td>
<td>( C_{size} )</td>
<td>0.723</td>
<td>0.7664</td>
<td>0.7637</td>
<td>0.938</td>
</tr>
<tr>
<td>Ref. II</td>
<td>( E_{rms} )</td>
<td>2.730</td>
<td>2.317</td>
<td>2.410</td>
<td>1.476</td>
</tr>
<tr>
<td></td>
<td>( C_{size} )</td>
<td>0.535</td>
<td>0.563</td>
<td>0.564</td>
<td>0.936</td>
</tr>
</tbody>
</table>

Fig. 10. Examples of the proposed active contour models.

Conventional, Greedy and Dynamic algorithm have unsatisfying results in Table 1 because of concavity problem and multiple objects. Accordingly, the effectiveness of the proposed method was verified based on a comparison with other conventional methods through objective validation and subjective consideration as regards the detection of a concave region and multiple objects. Thereafter, 12-bit quantized images, 512×512 in size, from EBT image equipment (Imatron, Inc.) were used to detect the contour of the pulmonary parenchyma in pulmonary EBT images. Figs. 11 and 12 shows the detected right and left pulmonary parenchyma from an initial contour when using the proposed solution for concave regions, and resulting 3-dimensional images.
Fig. 11. (a) and (b) examples of pulmonary EBT image using improved active contour model.

Fig. 12. 3-dimensional images of pulmonary parenchyma (a) bottom and (b) frontal views.

5. Conclusion

Conventional active contour models have weak points in relation to concave regions and initialization. Accordingly, this paper proposes a method that allows the contour to progress into a concave region by minimizing the summation of the internal energy controlled based on the movement of a perpendicular bisector by a rotational transform and the external energy generated from the image edge. Using this solution for concave regions, the contours of multiple objects are obtained by dividing the contours based on a comparison with a minimum interval for contours progressing between objects. The contour can be accurately detected by properly controlling parameter $\theta$ for the internal energy and parameter $\gamma$ for the external energy in relation to the features of the object. The proposed method was verified through objective validation and subjective consideration of the detection of concave regions and multiple objects. Consequently, it is expected that the proposed method can be efficiently applied to the early detection of pulmonary disease, the progress, and healing process through the detection of the pulmonary parenchyma region in medical images.

Acknowledgements

This work was supported by grant No. R01-2005-000-10140-0 from the Basic Research Program of the Korea Science & Engineering Foundation.

References