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## Lung Lesion Extraction Using Improved Toboggan Based Algorithm

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**Abstract:** The segmentation of lung lesions with an acceptable accuracy from computed tomography (CT) scans is more valuable for lung cancer research and can offer important information for clinical diagnosis and treatment by the doctors. It is a challengeable process to achieve a fully automatic lesion detection and segmentation with acceptable accuracy due to the various characteristics of lung lesions. Here, we propose an improved toboggan based growing automatic segmentation approach (ITBGA) which are automatic initial seed point selection, The new approach does not require any human interaction or training dataset for lesion detection, yet it can provide a high lesion detection sensitivity (98.35%). The results show a significant improvement in segmentation accuracy. The average time consumption for one lesion segmentation was under 9 seconds using proposed method. The improved toboggan based algorithm can achieve robust, efficient and accurate lung lesion segmentation in CT images automatically.

**Keywords:** CT (Computed Tomography), Seed Point Selection, Lesion Extraction, Improved Toboggan Based Growing Automatic Segmentation Algorithm (ITBGA)

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### I. INTRODUCTION

LUNG cancer is the major cause of cancer mortality around the world [1]. Up to 10 million patients in the world will die due to lung cancer in the year of 2030 in terms of the report from the World Health Organization [2]. Early prevention of lung tumour increases survival benefit improvements. With the help of the deep analysis of radiographic images can shows the microenvironment factors and the extent of intratumoral cells for personalized medicine [3][4], study of large numbers of image features extracted from computed tomography (CT) with high throughput can capture internal organs and cells in a non-invasive way, which is better than invasive biopsy based medical procedures.

It will be useful for medical research, computer-aided diagnosis or operational procedure, radiology and use for final analysis of surgery outcome as well. For this purpose, accurate Segmentation of lung Lesions is required. In older days the lung lesion segmentation can be carried out by experts with experience such as Radiologists define the lesion manually. It is a difficult task to obtain robust and efficient results for various reasons. The experts may underestimate or overestimate the lesion volume. Different manual delineations are also varying from one to another. Then the time consumption limits change the CT images to undetectable data due to fading, therefore a robust, high efficient and automatic lung lesion segmentation approach is required immediately. However, accurate segmentation of lung lesions by an automatic method is also a difficult process because of the various type and characteristics of the lesions. Due to the diversity of lung lesions, current segmentation accuracy is inadequate. The intensity, shape, and location of lung lesions change greatly because of the time period and the severity of the lesions. The intensity of lung lesions is sometimes close to the intensity of vessels, fissures or chest wall. But other times it is close to the intensity of lung fields, such as ground-glass opacity (GGO), which is not detected on CT scans that indicate a partial filling of air spaces as well as lung wall thickening or partial damage of lung alveoli [5]. Moreover, the influence of the inherent noise in CT images can also be significant. All these facts render that it is very challenging to achieve the precise delineation of lung lesions automatically.

This paper is organized as follows: section II describes the method used in this paper. Section III deals with the results and discussion and section IV Concludes the paper.

## II. METHODOLOGY

### A. Original toboggan

The toboggan algorithm was first proposed for image contrast enhancement in [6]. On the gradient image, a sliding direction could be determined by searching the minimum gradient magnitude of the neighborhoods of each pixel. Generally, the local minima pixels in the gradient image will be presented after repeating the search. Those pixels which “slide” to the same local minima will be labeled by the same mark. Thus, the gradient image could be segmented into a collection of small separated regions.

Steps:

Step1. Calculate the gradient image.

Step2. Scan the four/eight neighborhoods of each pixel in the gradient image one small area is enough for the selection of the lesion seed point, the toboggan method in this paper is designed to segment the image into small regions in the 2D view. The pixel would slide to its neighborhood with the minimum gradient value (if there is more than one pixel, the upper leftmost is obtained). The process will be repeated until it slides to the pixel with the local minimum. If the destination pixel is not labeled, a new label would be assigned to it.

Step3. Mark the pixels slide to the local minimum by the same label with the “minimum” pixel.

Step4. Repeat the process for all pixels. If a pixel is not labeled, its four neighborhoods (or eight) will be searched to find the local minimum. The process continues until all pixels in the image are segmented.

An overview of how the original toboggan approach works are shown in Fig (1). Where Fig. 1(b) is the small region circled by a black box in Fig. 1(a). The segmentation result with a sliding direction (triangular arrow flow) of each pixel using the original toboggan algorithm is presented in Fig. 1(b). Each small region circled by bold black lines will be marked by a unique label to further identify the targeting region. However, our improved toboggan algorithm can overcome some drawbacks of this conventional toboggan approach using a new algorithm for calculating the local minima, as shown in Fig. 1(c). The detailed explanation is presented in the next section. Unlike the elongated pulmonary vessels, the characteristic of the lesion is closer to a regular circular one. Thus, according to the shape characteristic, four neighborhoods searches could reduce the probability of the lesion pixels sliding into the lung field. Therefore, the four neighborhoods are used to detect the toboggan gradient magnitude minima in this paper.

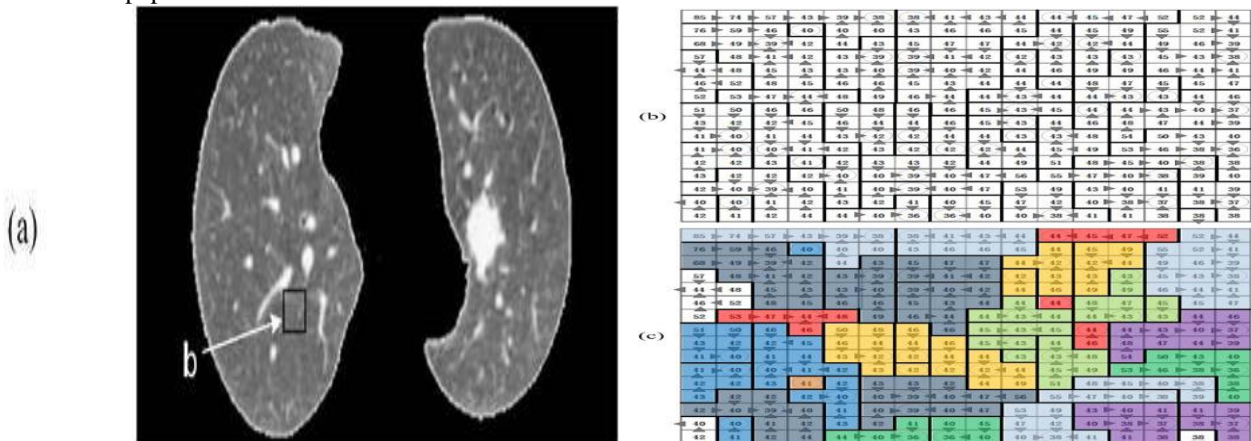


Fig. (1) .An example of the toboggan method. (a) The gradient image of lung parenchyma. (b) The illustration of the working mechanism of the original toboggan method using the magnification of a partial lung parenchyma (the black box in (a)). Each number is the gradient magnitude of one pixel. Bold black lines define small regions sharing the same minima pixels. Triangular arrow flow shows the slide direction of each pixel. The local minima pixels are shown with circles. (c) The illustration of improved toboggan method for finding the local minima pixels. Different from the original toboggan method, all small regions are categorized in the same colour once their minima pixels have the same gradient magnitude so that over segmentation can be effectively avoided.

### B. Improved toboggan algorithm

Multiscale Gaussian convolution could reflect image gradient changes in different direction. The different Gaussian convolution kernels could describe the gradient on each coordinate axis (X-axis, Y-axis or Z-axis) in [7] and [8]. The multi-scale Gaussian gradient could also give a more accurate description for the lung image compared with other gradient computation methods. The highlighted noise would be neglected by the improved toboggan algorithm after contrast enhancement using multi-scale Gaussian convolution. The derivative of the multi-scale Gaussian kernel is used for lung gradient calculation is

$$N\sigma(X,Y) = \exp \left[ -\frac{x^2+y^2}{2\sigma^2} \right] \dots\dots\dots (1)$$

The kernel is a two-dimensional (2D) discrete convolution function with a standard deviation of  $\sigma$ . The multi-scale gradient magnitude is given by  $\sigma$

$$G(x,y) = \max \left[ \sqrt{G\sigma(x,y)} \right] \dots\dots\dots (2)$$

$G\sigma(x,y)$  is a matrix of the gradient for pixels with the center  $(x,y)$ , where

$$G\sigma = I_{(a,b)} \times \left[ \left( \frac{\partial N\sigma}{x} \right)^2 + \left( \frac{\partial N\sigma}{y} \right)^2 \right] \text{-----(3)}$$

$(a, b)$  denotes the coordinate of the pixel and  $I_{(a,b)}$  is the intensity of a pixel  $(a, b)$  in the convolution kernel window. In this section, the gradient magnitude of all of the pixels is approximately  $[0,100]$  after multi-scale Gaussian convolution.

A gradient map of the lung parenchyma after the Gaussian convolution is shown in Fig. 2(a). The lesion has similar gradient magnitude with that of the vessels, fissures, bronchi, noise and other tissues. The original toboggan result is shown in Fig. 2(b), which produced serious over segmentation. Therefore, it cannot differentiate the lesion from the lung image. To overcome those challenges we present a toboggan gradient stack to calculate a new lung label image, which could exclude other tissues with a similar value to lesion on the gradient image. The toboggan gradient stack is used to store the local minima we searched for each pixel. The performance of the original and improved toboggan methods are compared through a simplified illustration in the Fig. 1(b) and (c). Instead of marking each small region with a specific label by the original method, small regions with the same minimum gradient value are marked as the same label, even when they are not morphologically connected, as shown in Fig 1(c). This approach can effectively minimize the over-segmentation. The example of lung segmentation result using the improved toboggan method is shown in Fig. 2(c). The mathematical process is as following.

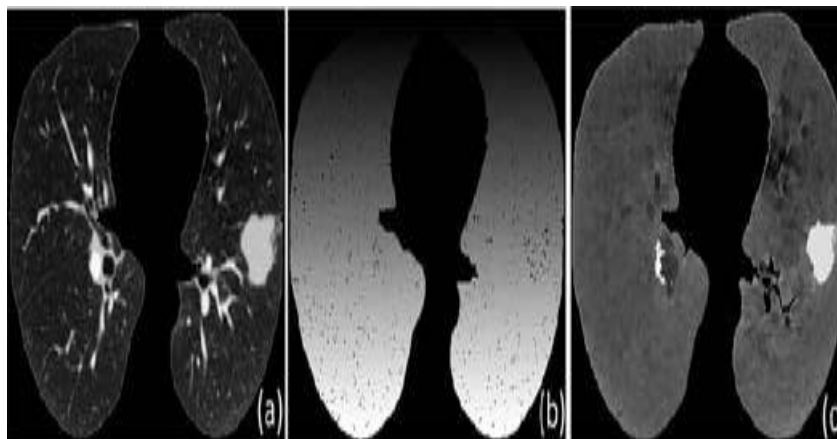


Fig.(2). The comparison of results by different toboggan methods. (a) Present a gradient image of lung parenchyma. (b) Shows the over-segmentation by the traditional toboggan method. The lung parenchyma is divided into more than 1000 patches. (c) Describes the result by the improved toboggan algorithm

For the improved toboggan, an empty stack is pre-defined to store the local minima gradient pixels. Each new local minimum gradient magnitude will be compared with all of the existing elements in the stack. A value in the stack with the maximum similarity to the new local minimum would be returned to mark the original source pixel. Otherwise, the new minimum will be pushed into the stack and used to label the source pixel.

In the new toboggan algorithm,  $L_{source}(i, j)$  denotes the value of  $(i, j)$  in the new label image of lung parenchyma.  $G_{source}(i, j)$  Represents the original gradient magnitude of  $(i, j)$ , where

$$SMax(ToboStack, G_{ToboMin}(i, j)) \text{-----(4)}$$

Represents the function where we traverse the toboggan stack to find the maximum similar gradient magnitude.  $TobogoStack$  is the toboggan gradient stack and  $G_{ToboMin}(i, j)$  means the minimum gradient value we searched for  $(i, j)$  by its four-neighbor hoods. The new label of  $(i, j)$  is defined as:

$$L_{source}(i, j) = G_{source}(i, j) * P + [SMax(ToboStack, G_{ToboMin}(i, j))]^2 * q \text{-----(5)}$$

Here we select the square of  $SMax$  to enhance the contrast between the lesion and lung field. For many lesions, the boundary points will vanish with the toboggan method as the boundaries are easily moved to their adjacent lung field. In order to achieve a more accurate lesion contour, these boundary points are kept by introducing  $p$  and  $q$  in the formula.  $p$  and  $q$  represent the weight of the two parts on the right side of the formula. In terms of a number of experiments on different lung field images, the optimal value of  $p$  is in the range of  $(0.0, 0.2]$  and is  $[0.8, 1.0)$ . Application of these two values can increase the weight of the original pixel gradient value and reduce the impact of noise. They are constrained with:  $p + q = 1$  ----- (6)

### C) IMPROVED TOBOGGAN BASED SYSTEM

The proposed method consists of 2phases: Seed point Selection & Lesion extraction. Fig. 3 presents the overview of the proposed method. A more detailed flowchart with figures for each step has been presented in this paper. The input of our algorithm is a slice of CT image containing lung lesion(s). For the first step, the algorithm proposed in [9] is applied to segment the lung parenchyma automatically. After that, a multi-scale Gaussian filter is applied to compute the gradient magnitude of each pixel in this lung parenchyma image. Then, the improved toboggan based algorithm is applied to the gradient image of lung parenchyma to detect the four-eight connected neighborhoods around each pixel for a destination pixel with the minimum gradient value. A specific mark will be targeted on the original pixel once its minimum is detected. After all of the pixels are labeled, those highlighted parts in the original lung parenchyma image such as vessels in the lungs and noise will be moved to the lower gray part (lung field) while the lesion is still highlighted. It means that only the lesion is left for automatic seed point selection and other parts such as vessels are avoided. As lung nodules are observed to have spherical shape but vessels have anisotropic shape, the elongated morphological characteristic of vessels is mainly responsible for its elimination. All the process in the first step is working on a 2dimensional CT slice. In the second step, the lung lesion is segmented by the automatic region growing method by means of sigma value given. So that the edge of the lesion can be detected more accurately on the original CT scans. Finally, in the lung lesion refining phase, a method based on lesion boundaries is provided to smooth abnormal regions around the lesion generation. By the multi-constraints, other lung tissues could be excluded on the original CT scans.

The contrast enhancement can be done by using multi-scale Gaussian convolution. The first-order derivative of the multi-scale Gaussian kernel is used for lung gradient calculation in our paper.

$$N\sigma(X,Y) = \exp \left[ -\frac{x^2+y^2}{2\sigma^2} \right] \text{-----}(7)$$

The Gaussian filter is used to remove the more noise in the image. The improved toboggan based algorithm is mainly used for seed point selection and the sigma value can be assigned improves the efficiency in detection of lesion region.

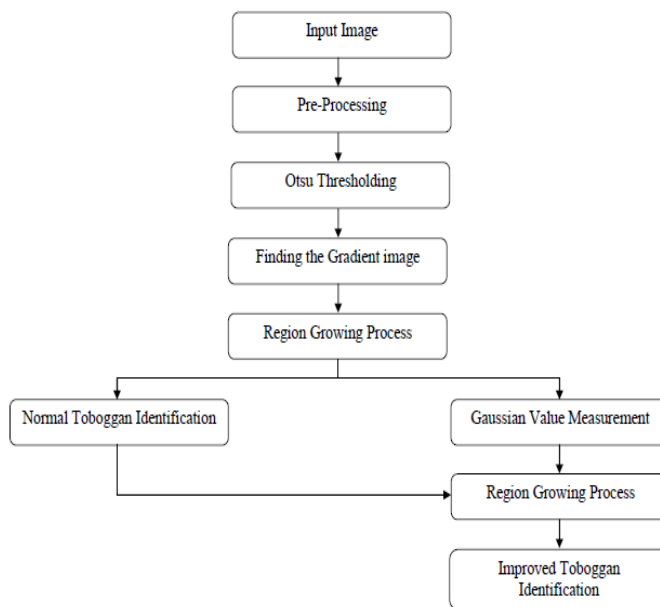


FIG 3) Block Diagram for Improved Toboggan based Identification of Lung Lesion

### III. RESULTS & DISCUSSION

#### A. Dataset

The ground truth image obtained was evaluated by means of confusion matrix datasets were used to evaluate the performance of our improved toboggan based method.

#### B. Evaluation metrics

Confusion matrix is used to measure the lesion segmentation accuracy by means of true positive, true negative, false positive, false negative

$$\text{Accuracy} = \frac{(\text{True positive} + \text{True Negative})}{(\text{True Positive} + \text{False positive}) + (\text{False Negative} + \text{True negative})} \text{-----} (8)$$

To demonstrate the accuracy of the new algorithm, we tested the segmentation of different types of pathological lungs as discussed in the introduction using confusion matrix

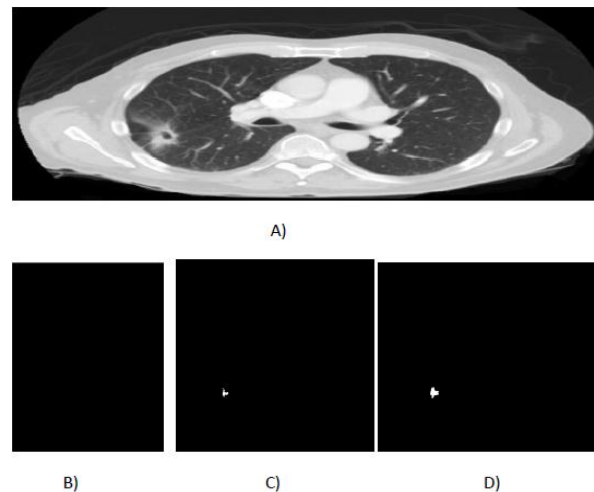
In this paper, we present an automatic, stable and quick-response lung lesion segmentation algorithm, the initial seed points were first detected using an improved toboggan method for the lesion segmentation. Then, the lesion was extracted by an automatic growing algorithm. Finally, the segmentation result was optimized by a lung lesion refining method.

The important component of this work is that it does not require any training datasets or human interactions for lesion seed point detection, while it could obtain more accurate segmentation results compared with other methods, especially for ground-

glass opacities. Besides, compared with the previous lung lesion segmentation algorithms, better performance was obtained with improved time efficiency by our method. As the new method has a variety of advantages for the segmentation of lung lesions, it will be further examined in a clinical environment and can also be applied as a reference.

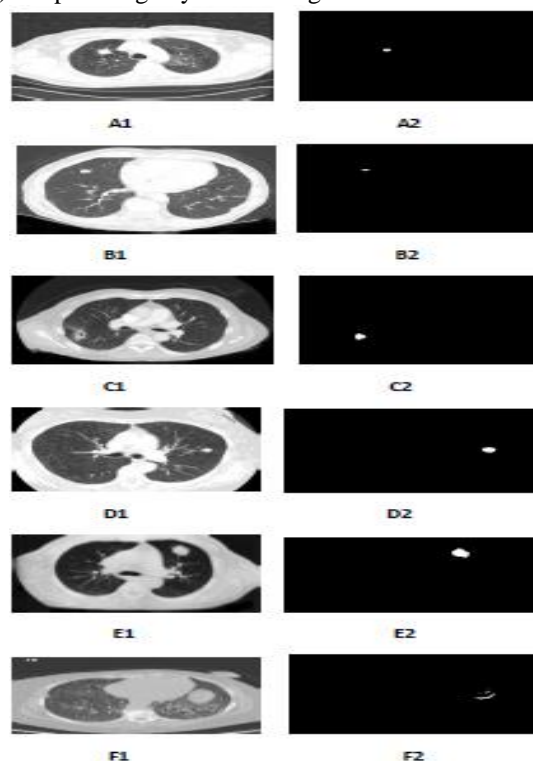
For the tissues connected to the adjacent lesion with a similar intensity of pixels, a high degree of recognition is lacking by the proposed method. This is the main reason for the poor segmentations. Our future work will focus on the accurate boundary detection for a cavity in the lesion and juxta-vascular lesions.

As for lesion segmentation, precise lung parenchyma segmentation is another issue we should address in the future. Generally, the segmentation result of lung parenchyma is the basis of lesion extraction, so the lung parenchyma should include the lesions wherever they located.



**Fig 4) shows the comparison of various methods**

A) Input CT image B) Output image by FCM (FUZZY C-MEANS) algorithm. (The lesion cannot be able to be detected by FCM) C) Output image by TBGA algorithm. D) Output image by ITBGA algorithm.



**Fig 5) shows the various CT (COMPUTED TOMOGRAPHY) images obtained by ITBGA.**

A1, A2) shows the input and output of GGO type lesion, B1, C1) shows input of solid nodule and B2, C2) shows the output for solid nodule D1, D2) shows the input and output of juxta-vascular type lesion E1, E2) shows the input and output of solitary nodule F1, F2) shows the input and output of lesion with juxta-pleural type.

The major contribution of the proposed ITBGA method is the lung lesion segmentation. With accuracy rate up to 98%. This paper proposed an automatic method for the lung lesion seed point(s) initialization and lung lesion segmentation was performed

without any training datasets or human interactions. Another contribution is the segmentation of ground-glass opacities. In the compared methods, the advantage of the LS algorithm from Li [9] is that it could represent the outline of GGO, as it is insensitive to the difference of pixel intensity. However, the lesion segmentation may not be completed if the number of evolution becomes less. SGC could access the lesion outline in a quicker response than the LS, but it is sensitive to juxta-vascular lesions.

The proposed algorithm could find clearer lesion boundaries for ground-glass opacities without the disadvantages of time-consuming and easily included of blood vessels include the lesions wherever they located.

### CONCLUSIONS

This paper proposes an automatic method for the lung lesion seed point(s) initialization and lung lesion segmentation was performed without any training datasets or human interactions. The main part of work is the segmentation of ground-glass opacities. Compared with the various lung lesion segmentation algorithms, better performance was obtained with improved time efficiency by proposed method. The proposed method has a variety of advantages for the segmentation of lung lesions; it will be further examined in a clinical environment and can also be applied as a reference.

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