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COMPUTER AIDED EVALUATION OF PLEURAL EFFUSION USING CHEST CT IMAGES

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Abstract

A pleural effusion is a condition where there is a buildup of abnormal fluid within the pleural space. This paper presents an automated method to evaluate the severity of pleural effusion using regular chest CT images. First the lungs are segmented using region growing, mathematical morphology and anatomical knowledge. Then the visceral and parietal layers of the pleura are extracted based on anatomical landmarks, curve fitting and active contour models. Finally, the pleural space is segmented and the pleural effusion is quantified. Our method was tested on 15 chest CT studies. The automated segmentation is validated against manual tracing and radiologist's qualitative grading. The Pearson correlation between computer evaluation and radiologist's grading is 0.956 ($P=10^{-7}$). The Dice coefficient between the automated and manual segmentation is 0.74 ± 0.07 , which is comparable to the variation between two different manual tracings.

Keywords

Pleural Effusion; CAD; Segmentation

1. INTRODUCTION

A pleural effusion describes the condition of fluid buildup within the pleural space of the lung cavity, usually as a symptom of a greater illness, such as ventricular failure, liver cirrhosis, or malignancy, and can be split into two classes based on how the fluid originates [1]: transudates come from changes in hydrostatic pressure, where the fluid is pushed into the pleural space from elsewhere; or exudates, where the fluid is created by the pleural surface itself. Excessive amounts of such fluid can impair breathing. Knowing the location, and especially the volume, of a pleural effusion can assist a physician in determining the severity of a condition, or whether to perform a biopsy on the pleural effusion.

Pleural effusion can be detected via a number of noninvasive methods, including chest radiographs, CT chest studies, and ultrasound. Ultrasonic methods offer the best flexibility and portability, as well as more accurate volume measurements when compared to chest radiography; however, for best location of the pleural effusion coupled with accurate volume measurement, chest CT scans are the norm [1]. With regard to CT chest scans, the majority of work on pleural effusion detection and measurement has been concentrated towards either defining features for use in manual separation of pleural effusions from surrounding tissues or other irregularities such as ascites [2], or towards better measurement of a defined volume [3]. Many of these did not measure the volume directly. The system in [3] did not directly count the number of pixels within the area of the pleural effusion. It instead relied on measurements of specific attributes, such as length and depth of the effusion. It was found that despite not directly measuring the cross sectional area, the measurement still correlated

well with the actual volume, as determined by radiologist estimation. However, these versions of volume measurement software still require a radiologist to interpret the CT images and manually draw in areas determined to be pleural effusions to be measured, an often time consuming task.

What is desired is a computer aided diagnostic system that not only determines the volume of a defined space, but one that will identify areas of pleural effusion and select the correct volumes without radiologist input. This would not only reduce the time required per CT series; if the accuracy of the system were sufficiently high, it could also reduce the number of errors in diagnosis. The aim of this study was to develop such a system and test it in a reasonable number of cases to determine its effectiveness.

Automated pleural effusion evaluation in CT images is not a trivial task due to the following reasons: 1) the pixel intensity of the pleural fluid is very close to that of the soft tissues and the compressed lung tissues; 2) the boundary of the pleural space is irregular and usually ambiguous. Figure 1 shows examples of pleural effusion.

2. MATERIALS AND METHODS

The outline of our method is illustrated in Figure 2. Given a chest CT data set, the images are preprocessed using an anisotropic diffusion filter to reduce the noise. Then 3D lung segmentation is conducted to mask the lung region and separate the left and right lungs. After that, the visceral and parietal layers of pleura are extracted. Finally the pleural effusion is measured and evaluated.

2.1 Preprocessing

A preprocessing step is first conducted to reduce the noise and artifact in the image. Anisotropic diffusion is a nonlinear method of smoothing regions in an image while preserving the edges between regions. At its most basic form, the filter forces the pixel intensities in each region of the image to migrate towards the average in each region. The general form of the filter is:

$$\frac{\partial}{\partial t} I(x, t) = \nabla \cdot (f(x, t) \nabla I(x, t)) \quad (1)$$

where $I(x, t)$ represents the CT image, x refers to the pixel coordinate of the image, and t refers to the iteration step (default value is 0.25); $f(x, t)$ represents the diffusion function, which in this work is defined as [4],

$$C(x) = e^{-\left(\frac{\|\nabla I(x)\|^2}{K}\right)}, \quad (2)$$

where K represents the diffusion constant (default value is 3). The result of anisotropic diffusion is shown in Figure 3b.

2.2 Lung Segmentation

A custom segmentation technique based on region-growing and mathematical morphology has been developed to segment the left and right lungs. First, the trachea is located and segmented out. By using the segmented position of the trachea, two seed points are located to each side of it. Those points represent a possible point within the lungs. Then, by using a 3D region-growing algorithm, the seeds are expanded to segment the actual area and space of the lungs. Finally the segmentation is refined using mathematical morphology to close

gaps and holes inside the lung and along the boundary. As part of the segmentation process, we distinguish between the left and right lung. Details of the lung segmentation algorithm can be found in [5]. The lung segmentation routine returns a mask of the lung area $S(x,y)$, where $S(x,y)=1$ for lung pixels and $S(x,y)=0$ otherwise (Figure 3c).

2.3 Visceral and parietal pleura extraction

The pleural space is the space between the visceral and parietal layers of the pleura, which are serous membrane structures. The visceral pleura (inner layer) cover the lungs, and the parietal pleura (outer layer) are attached to the chest wall (Figure 1). Most of the pleural fluid is accumulated at the bottom of the pleural space due to the gravity. In order to segment the pleural space, the visceral and parietal pleura need to be extracted. The extraction algorithm is applied to the left and right pleural spaces separately.

We devise a three-step routine to extract the visceral layer. First, the initial layer is detected at the boundary of the lung; second, a b-spline curve is fitted to the initial layer; and third, an active contour model is applied to refine the layer.

The initial visceral layer is located at the last lung boundary point for each y scan-line since the fluid is accumulated at the bottom of the lung. The (x,y) axis is marked on Figure 4a. This process can be formulated as,

$$VL(x)=\arg \max_{y, B(x,y)=1} (B(x,y))$$

$$B(x,y)=\begin{cases} 1 & \text{where } S(x,y)=1, S(x,y+1)=0 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

here $B(x,y)$ is the lung boundary map, $S(x,y)$ is the lung segmentation mask. $(x, VL(x))$ is the initial value for the visceral layer, which is shown in Figure 4a. The initial value is then fitted into a smooth b-spline curve [6], written as

$$N_{i,d}(t)=\frac{t-t_i}{t_{i+d}-t_i}N_{i,d-1}(t)+\frac{t_{i+d+1}-t}{t_{i+d+1}-t_{i+1}}N_{i+1,d-1}(t)$$

$$C(t)=\sum_{i=0}^n P_i N_{i,d}(t) \quad (4)$$

Here $C(t)$ is the fitted curve, $T=\{t_0, t_n\}$ are evenly distributed internal knots, $N(t)$ are the basis functions, d is the degree of the curve (default value is 5), and $P_i=(x, VL(x))$ are the control points from the initial boundary. Then an active contour model [7] is employed to refine boundaries. Using the b-spline curve as the initial contour, several forces work together to drive the active contour to its destination. The forces can be expressed as,

$$F=w_{in}F_{internal}+w_{im}F_{image} \quad (5)$$

where $F_{internal}$ is the spline force of the contour, and F_{image} is the image force, and w_{in} and w_{im} are the respective weighting parameters. The internal force $F_{internal}$ can be written as:

$$F_{internal}=\frac{1}{2}\int_0^1(\alpha(s)|c'(s)|^2+\beta(s)|c''(s)|^2)ds \quad (6)$$

where $c(s)$ is the curve representing the contour, $c'(s)$ is the first order derivative of $c(s)$, and $c''(s)$ is the second order derivative of $c(s)$. The spline force is composed of a first-order term controlled by $\alpha(s)$ (default=0.5) and a second-order term controlled by $\beta(s)$ (default=1). F_{image} are forces derived from the image to attract the contour to image features such as edges, iso-values, or boundaries. In our method, we use the gradient of the edge map as the image force, i.e.

$$F_{image} = \vec{g}(|I'(x)|) \quad (7)$$

where $\vec{g}$ is the gradient, $I'(x)$ is the first order derivative of image I , $|I'(x)|$ forms the edge map. Figure 4b shows the extracted visceral pleura.

The parietal layer serves as the lower border of the pleural space. It is attached to the inner wall of the rib cage. We use a similar three-step routine for the parietal pleura extraction. First, landmark points on the inner rib cage are detected; second, a Bernstein polynomial is fitted to the landmarks; and third, an active contour model is applied to refine the layer.

Ribs are used as the landmarks for the parietal layer. We model the ribs as an elongated slab with high pixel intensity (Figure 4c). For every point (x_i, y_i) on the visceral layer, we search in the space below it to locate the best matched rib model. The searching process can be written as,

$$\arg \max_{y_i^u, y_i^l} (g(I(x_i, y_i^u)) - g(I(x_i, y_i^l)))$$

where $I(x_i, y_i^u) > th, I(x_i, y_i^l) > th, t_{min} < y_i^u - y_i^l < t_{max}$

(8)

here $I(x, y)$ is the image intensity, $g(I(x, y))$ is the image gradient, th is the bone intensity threshold (default: 300HU), t_{min} and t_{max} is the range of rib width (default values: 10 and 20 pixels). The upper border points (x_i, y_i^u) are collected as landmarks (Figure 4d). The landmarks could be missed at some rib locations, or they could even be at wrong locations (e.g. shoulder bones in Figure 4d). We fit a 5-degree Bernstein polynomial to interpolate missing landmarks and eliminate wrong ones. The polynomial is written as

$$y = B(a_0, \dots, a_5; x) = \sum_{k=0}^5 a_k \binom{5}{k} (1-x)^k x^{5-k} \quad (9)$$

The fitting operation is used to find a_k which minimizes the least square metric $\sum [y_i - B(a_0, \dots, a_5; x_i)]^2$, here (x_i, y_i) are the landmark points. The curve fitting is iterated three times and each time outliers (those far from the fitted curves) are eliminated from next iteration (Figure 4e). The curve is then used as the initial value for an active contour model (Equation 5) to refine the parietal layer (Figure 4f).

2.4 Pleural effusion measurement

We connect the two endpoints of the visceral layer and the parietal layer and employ a scanline algorithm [8] to fill the space. The pixels in the filled space belong to the pleural space. The procedure is repeated for all slices and the total number of pixels is counted as the volume of the pleural effusion. The ratio of the pleural effusion volume versus the lung volume is also computed. Figure 5a shows one automatically detected pleural effusion.

3. RESULTS

Fifteen patients (Age 32–79 yrs, mean 52.4 yrs) with at least moderately sized pleural effusions (as described in the radiology report) were selected for the evaluation of our method. The chest CT scans had 5mm slice thickness and spacing. The in-plane spacing ranged from 0.63mm to 0.88mm.

An operator manually traced out the apparent pleural effusions on screen. The Dice coefficient was then computed between the manual tracing and the computer segmentation,

$$DC = \frac{2\|V_c \cap V_m\|}{\|V_c\| + \|V_m\|} \times 100\% \quad (10)$$

here V_c is the set of computer segmented voxels, and V_m is the set of all manually traced voxels, $\|\bullet\|$ is the number of voxels in a segmentation. The manual tracing was conducted twice at different times. Figure 5 shows examples of the computer segmentation and two manual tracings. Table 1 summarizes the Dice coefficients. The Dice coefficient between the computer segmentation and the manual tracings is comparable to the variation between two manual tracings.

For each study, an experienced radiologist visually examined the CT images and subjectively graded the severity of pleural effusion in the left and right lungs separately. The grade ranged from 0 to 4, where 0 indicates no pleural effusion and 4 indicates severe pleural effusion. Among the thirty lungs (15 patients, left and right lungs), seven were scored as grade 0, nine as grade 1, seven as grade 2, five as grade 3 and two as grade 4. Figure 6 shows a scatter plot of the radiologist grades versus the ratio of computed pleural effusion volume/lung volume. The regression analysis shows that the Pearson correlation is 0.956 and $P(T \leq t) = 10^{-7}$.

4. DISCUSSION AND CONCLUSION

There are several limitations in the current program. The segmentation is conducted on each 2D slice, which makes it difficult to maintain the continuity of the pleura surface between slices. A 3D surface model is desired to refine and improve the segmentation. The method currently relies on the bottom of the lung for the initialization of the pleural space. In case where the lung is totally compressed, more sophisticated initialization based on texture features may be needed.

While draining the pleural fluid would be the best method of verifying accuracy of the program, this was not possible due to the fact that the image series used were all from several months prior, and the patients had already been discharged. A future study should look into finding several current patients and going through the process of draining their pleural effusions immediately after imaging. The system could possibly be modified for detection of malignancy, if a link between malignancy of a pleural effusion and pixel intensity or appearance could be found.

Our program should help clinicians by reducing the time spent in identifying and measuring the size of pleural effusions. It is no longer necessary for a radiologist or technologist to painstakingly go through each CT image series slice by slice and select the pleural effusion to be measured. Furthermore, the visual grading is subjective and rough, and big variation may occur for different manual segmentations. This technique could be used to quickly give an estimate of pleural effusion size, giving physicians another diagnostic tool. Our

validation showed that the computer pleural effusion evaluation is highly correlated with radiologist grading, and the automated segmentation is comparable to the manual ones.

Acknowledgments

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Figure 1. Pleural effusion examples

a) normal lung, b) minimal pleural effusion, c) severe pleural effusion

Figure 2. System overview

Figure 3. Preprocessing and lung segmentation

a) original image, b) after anisotropic diffusion, c) lung segmentation mask, green: left lung area, red: right lung area

Figure 4. Visceral and parietal pleura extraction

a) initial value of visceral pleura (green), b) fitted visceral layer (red), c) rib model, d) landmarks for parietal pleura (blue), e) Bernstein curve fitting (red), results of three iterations, f) final parietal layer (green)

Figure 5. Computer segmentation versus manual tracing

a) computer segmentation (yellow), b) manual tracing 1 (pink), c) manual tracing 2 (pink).

Figure 6. Radiologist grades versus computer evaluation

Table 1
Dice coefficients between computer and manual segmentations

M1: manual 1, M2: manual 2, CP: computer

Dice Coeff	Mean	Stdev	Max	Min
M1 vs. M2	0.81	0.08	0.92	0.61
CP vs. M1	0.74	0.07	0.85	0.60
CP vs. M2	0.71	0.09	0.85	0.51