Three Cuts Method for Identification of COPD

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Received: 2 Nov. 2011; Received in revised form: 15 Sep. 2012; Accepted: Oct. 2012

Abstract- Chronic obstructive pulmonary disease (COPD) consists of emphysema and chronic bronchitis, which are lung diseases that block airflow and cause a huge degree of human suffering. A new method for identifying and estimating the severity of COPD from three-dimensional (3-D) pulmonary X-ray CT images is presented in this paper which is helpful for the treatment plan and early diagnosis. The proposed method consists of five main steps. First, corresponding positions of lungs in the inspiration and expiration states are found based on the anatomical structures. Second, lung regions are segmented in the CT images using active contours. Third, the left and right segments of the lungs are separated using a sequence of morphological operations. Forth, the volumetric variations of three main cuts which are selected by a feed-forward neural network are found based on the inspiratory and expiratory states. Fifth, a pattern classifier is used to diagnose the severity of the disease. To evaluate the proposed method, twenty patients with variable severity of air-trapping and twelve healthy adult subjects were enrolled in this study. A mathematical model was developed to make a connection between volume variations and the severity of disease. Based on the results, the sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV) and the accuracy of our method for the right regions were 81.6%, 80.5%, 87.5%, 72.5% and 81.3%, respectively. These parameters for the left regions were 90%, 83.3%, 90%, 83.3% and 87.5%, respectively. The proposed method may assist radiologists in the detection of COPD and Asthma as a computer aided diagnosis (CAD) system.

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Keywords: Air trapping; Chronic Obstructive Pulmonary Disease (COPD); Computer Aided Diagnosis (CAD); Artificial Neural Network; Pattern Classifier; X-ray Computed Tomography (CT)

Introduction

Asthma is an inflammatory disorder of the airways, which causes swelling and narrowing of the airways. Asthma and allergies often go hand-in-hand. About 70% of asthmatics also have allergies (1). Chronic obstructive pulmonary disease (COPD) is a disease characterized by chronic airflow obstruction which includes emphysema, chronic bronchitis, and small airway disease (2). COPD is the fourth leading cause of death in the U.S. and is projected to be the third leading cause of death for both males and females by the year 2020 (3). Early detection is one of the most important factors contributing to a longer and healthier lifestyle. Pulmonary function tests are the primary diagnostic tools for COPD after a complete medical history and physical examination.

Computed tomography (CT) has been long known as the main imaging approach for lung diseases such as COPD and asthma which enables early disease detection. Due to many parenchymal structures, it is sometimes extremely difficult to decide whether or not a CT or high resolution CT (HRCT) is abnormal. Image interpretation in this scenario depends on the doctor’s experience and would be subjective.

Correlations between the HRCT and pulmonary function tests have been shown in many studies. In (4), a comparison between findings of inspiratory and expiratory HRCT and pulmonary function tests is done. Analyzing the correlation of the inspiration and expiration states in CT images can be helpful for the evaluation of severity of asthma and COPD based on the physician’s perceptions and literature reviews.

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Reference (5) reports the measurements of lung attenuation in the patients with less severe COPD can be well reflected in the inspiration state. In contrast, for patients with severe COPD, expiration indicates better results compared to the inspiration state. Zaporozhan, et al (6) used paired inspiratory and expiratory volumetric thin-slice CT scan for emphysema analysis. Volumetric analytic methods have been presented by Hosseini, et al. to detect the severity of COPD (7-10). They have developed a computer-aided diagnosis (CAD) system for COPD detection using volumetric variations of lung body. It is shown in (11) that the volumetric cluster analysis provides deeper insights into the local hyperinflation and expiratory obstruction of large emphysematous clusters.

In this paper, we present an automatic method for the evaluation of air-trapping to detect and score the severity of asthma and COPD in the lung CT. Due to air trapping, asthma and COPD in severe cases cause the loss of lung’s elasticity. COPD reduces maximum expiratory flow by decreasing the elastic recoil force available to drive air out of the lungs. Radiologists diagnose COPD in CT images visually. This is difficult, time consuming, and subject to human errors. To address these challenges, an automatic method to score lung’s structural variation is developed in CT as it reflects elasticity and air-trapping. For this purpose by using an artificial neural network, three cuts (slides) of the lung which are more informative and indicate the disease more efficiently are extracted. Because of the large number of images generated by CT, developing CAD systems to assist radiologists in the detection of COPD would be helpful. In this study, a CAD system is designed to assess asthma and COPD in the CT images of the lungs.

Materials and Methods

Subjects

The thorax CT scan images were acquired at the Noor Medical Imaging Center, Tehran, Iran using a Siemens High Resolution CT scanner (Sensation 64). Thirty two subjects were enrolled in this study. In a cross sectional study, we evaluated air trapping in two groups of twenty patients (mean age, 56 years; range, 35-88 years) and twelve healthy subjects (mean age, 41.3 years; range, 22-53 years). About 41% of the subjects were female and about 59% of the subjects were male. They were imaged between November 2009 and March 2011. All patients involved in the study were under observation by an expert pulmonologist. The patient group in this study consisted of the subjects who had air trapping (asthma or COPD) according to its accepted definition who were visited at the radiology and pulmonary clinic of Noor Medical Imaging Center. Asthma and COPD were diagnosed by clinical symptoms, medical history, physical findings, and pulmonary function tests based on the guidelines of the American Thoracic Society.

The voxel size was 1x1x3 mm. The scanning voltage and current was 120 kV and 254 mA. In each case, the thorax scan was performed from the lung apices through the level of the adrenal glands at full inspiration and was repeated at full expiration. The mean breath-hold was 7 seconds for one scan. All imaging was performed with a collimation of 16x1.25 mm, table feed of 30 mm/rotation, and rotation time of 0.6 second/360° tube rotation with a standard reconstruction algorithm. The scanner was subject to a weekly quality assessment with a phantom check including uniformity, linearity, and noise. Air and water phantoms were used to calibrate the CT scanner. The study was approved by the local ethics committee and written informed consents were also obtained from all of the subjects. All aspects of the study were conducted according to the declaration of Helsinki.

Methods

The greater degree of air trapping, airway closure and increased wall thickness may be an indicator of more extensive disease progression of asthma and COPD. Total lung capacity (TLC), residual volume (RV), and functional residual capacity (FRC) are all characteristically increased in COPD and are related to the degree of hyperinflation of the lungs. However, when there is predominantly emphysema, the volumetric variation is less. Due to the above facts, our method finds volumetric variation of the separated lungs to detect and stage air trapping as an indicator of asthma and COPD. Because distal airways normally have the greatest compliance, it is probable that decreased volumetric variation (increased air trapping) is an indicator of more extensive disease progression. As shown in Figure 1, our method consists of five main steps: a matching between inspiration and expiration slices; a segmentation step to extract the lungs; a separation step to separate the right and left lungs; a volumetric variation evaluator for finding and comparing elastic recoil; and a pattern classifier for categorizing the results into normal and patient cases.
Identification of corresponding images

Each frame shows particular anatomical structures. Spatial properties of organs are typically dependent upon, and described relative to one another. When we evaluate all CT slices, the method is fully automatic and does not need to find the corresponding images of the inspiratory and expiratory states (12). By evaluating all of the slices, the result is more sensitive but it has some disadvantages such as a longer imaging acquisition, a higher radiation dose, and a longer computation time. Therefore as shown in Figure 2, we have used a feedforward neural network to find those CT slices which are more informative and demonstrate the abnormality more than others. Based on the results and medical surveys, three slice of the lungs which indicate disease and air-trapping more than others were selected for parenchyma variations. These three cuts which are the upper, middle, and lower parts of the lungs have the
most significant impact on volumetric variation test. Therefore, we used only these cuts for reducing the time of computation. In addition, if this test is accepted as a regular test, it only needs to scan patients in these three cuts so the radiation dose and the exposure time of the CT scans are significantly reduced. In our study, all of the subjects were imaged for their routine diagnosis procedure and they were not exposed to additional radiation for this research. We need to analyze a same slice’s position for a patient in the inspiratory and expiratory states. For finding the corresponding slices, we used anatomical structures such as the aortic arch and carina trachea (13). The aortic arch is the curved portion between the ascending and descending portions of the aorta. The carina is the apex of the bifurcation point of the trachea located at the lower border of the T5 vertebra. The third cut for our analysis would be 5 cm lower than the carina cut (Figure 3).

Segmentation of lung structures

Success of volumetric methods depend on accurate segmentation of the lungs. There are many segmentation algorithms in the literature. Various lung segmentation methods are proposed for specific applications.

In recent years, computer assisted segmentation of pulmonary CT images have been done using semi-automatic and automatic techniques. Active contour (snake) models work based on minimizing an energy function consisting of an external force and an internal force which are extensively used in the medical image processing applications. A modified active contour without edges (14) is used in this study for lung segmentation at full inspiration and expiration states (15). Figure 4 shows a transverse CT slice of a healthy subject and its segmentation result approximately at the carina cut.

Separation of the right and left lungs

Because COPD may only exists in one of the lungs, we assess each side separately. The goal of the lung separation step is to separate the right and left lungs. The anterior and posterior junctions between the left and right lungs may be very thin with low contrast in the CT images. Some morphological operations to separate the right and left lungs have been used by Shiying et al. (16). Dynamic programming is applied to find the maximum cost path through a graph with weights proportional to the pixel gray-levels in some papers. Hu and Hofmann (17) provide an automatic method for separation of the left and right lungs. In their method, the lungs are separated by a sequence of morphological operations while dynamic programming is used to smooth irregular boundaries.

For separation of the lungs, we used a combination of labeling of the connected components in 2D binary images with the morphological operations. Connected components are useful for all slides in which the anterior and posterior junctions between the left and right lungs are not very thin. Morphological erosion is applied to separate the right and left lungs. Then, a conditional dilation is used to restore the approximate original boundary shape, without reconnecting the two lungs (16,17). Erosion morphology shrinks an image by selecting the minimum value of all pixels in the neighborhood of the input pixel. On the other hand, dilation morphology expands an image by selecting the maximum value while the structuring element defines the neighborhood of the pixel of interest. We used four connected (diamond-shaped) binary structuring elements; the results are shown in Figure 5.

Evaluation of volumetric variations

Resistance of small conducting airways and increased compliance of the lung and the lung’s elastic recoil force cause airflow limitation in asthma and COPD. The changes of airway luminal area between inspiration and expiration were strongly related to airflow limitation (18). As such, in asthmatic and COPD patients, airflow and volume variations between inspiratory and expiratory states are less than normal cases. In this paper, the volume variation of the lungs in two stages of inspiration and expiration is used to indicate the lung elasticity. This elasticity shows the air trapping in the lungs so it is calculated to diagnose the abnormality. The volume changes in the defined three cuts are extracted in this method.

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Figure 3. Slices used for the 3 cuts method.
A feed-forward artificial neural network was used for finding these cuts. Different cuts of the case group and some other accepted subjects were assigned as input values to the neural network. Based on the results, three cuts of the lung which are indicative of disease more than others were selected for parenchyma variations. To have the same form of variation, the effects of age, height, weight, and sex should be removed. Therefore, for the purpose of normalization, we used the inspiration area as the reference. Figure 6 shows the structural variation for separated lungs between inspiration and expiration states at the carina cut.

Figure 4. Left: A transverse CT slice of a healthy subject approximately at the carina cut. Right: The segmentation result.

Figure 5. Left: Before separation. Right: After separation.

Figure 6. Left: Comparing the structural variation in inspiration and expiration for in the left lung. Right: The result in the right lung.
Classification of patterns

The Bayes pattern classifier is developed for classification of the extracted feature. Pattern classification is about assigning labels to objects and objects are described by one or a set of measurements called features (19). The structural variation that shows the air-trapping in each cut is used as the classification feature into two classes of normal and patient subjects. Accurate diagnosis in the proposed method is depended to the accurate classification. Therefore, different classifiers have been tested for this study and Bayes classifier is selected based on the results. We wish to minimize the probability of making an error. For this purpose, the Bayes rule is implemented to assign datasets to one of the two classes. The assumption of Gaussian distribution is used for the data set.

Statistical analysis

We used t-test to assess whether the means of the two groups of normal and patient are statistically different or not. Table 1 shows the mean and the standard deviation (SD) for each classes. Table 2 shows the results for t-test by the assumption of 0.05 for alpha (P < 0.05 were considered statistically significant). Statistical analysis was performed using the MATLAB R2010a software. As shown in Table 2, the means of the Gaussian distributions for the normal subjects and the patients are different.

Results

The proposed method is applied to each lung in the three cuts of the CT images. The samples are labeled by an expert radiologist. Figure 7 shows the normal distribution for the data sets of two classes in the right and left lungs. The hard threshold that minimizes the probability of making an error is found. The severity of disease is indicated by the Euclidean distance from the hard threshold. If the classifier assigns a pattern to a class when it actually belongs to another class, an error occurs. To estimate the error, the classifier is applied on all objects in a labeled data set and the proportion of misclassified objects is found. The errors of applying the Bayes classifier are given in Table 3 as a misclassification matrix or confusion matrix.

The Bayes decision threshold for the right lung is 31.16 and for the left lung is 30.05 (Figure 7). It should be noted that other threshold metrics can be used in the Bayes decision rule to minimize the reject option and risk. The sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV) and the accuracy of our method for the right lung region were 81.6%, 80.5%, 87.5%, 72.5% and 81.3%, respectively. The parameters for the left lung region were 90%, 83.3%, 90%, 83.3% and 87.5%, respectively. For showing the relationship between the right and left regions, a scatter plot is used in Figure 8. It shows the strength, shape, and presence of outliers.

Figure 7. Left: Normal distributions for the left lung. Right: Normal distributions for the right Lung.
Our study is different from previous studies in use of materials and methods. Hosseini et al. assessed lung volumetric variation for the detection of COPD (15). The proposed method finds volumetric variations of the lungs from inspiration to expiration states in all cuts. In (20), a comparison between expiratory and inspiratory states of CT images is done to provide an objective criterion for the severity of pulmonary emphysema. They compared the image gray levels but the proposed method is manual. Hosseini et al. suggested a novel method for designing a CAD system for the evaluation of COPD in CT images (21). The computation time and the exposure dose were the challenges in the previous studies. In this study, we proposed a method to address the existing challenges and the efficiency of automatic diagnosis is improved. In sum, the proposed method is able to estimate air trapping in the lungs from CT images without human intervention.

**References**


**Figure 8.** The relationship between the right and left lung structural variation in extracted normal and patient classes.

**Table 1.** Mean and STDEV of the volumetric variation in three cuts.

<table>
<thead>
<tr>
<th>Group</th>
<th>Sample Size</th>
<th>Left Lung Mean</th>
<th>Left Lung SD</th>
<th>Right Lung Mean</th>
<th>Right Lung SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>12</td>
<td>39.76</td>
<td>16.81</td>
<td>40.87</td>
<td>14.87</td>
</tr>
<tr>
<td>Patient</td>
<td>20</td>
<td>18.44</td>
<td>13.14</td>
<td>20.83</td>
<td>12.59</td>
</tr>
</tbody>
</table>

**Table 2.** The t-test results.

<table>
<thead>
<tr>
<th>Region</th>
<th>t-test Value</th>
<th>Degrees of Freedom</th>
<th>P-value</th>
<th>Difference of the Means</th>
</tr>
</thead>
<tbody>
<tr>
<td>Left</td>
<td>3.81</td>
<td>86</td>
<td>2.6e-004</td>
<td>yes</td>
</tr>
<tr>
<td>Right</td>
<td>3.38</td>
<td>87</td>
<td>0.001</td>
<td>yes</td>
</tr>
</tbody>
</table>

**Table 3.** Confusion matrix for the 3 cuts method (with hard threshold).

<table>
<thead>
<tr>
<th>Confusion Matrix</th>
<th>True class</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Normal</td>
</tr>
<tr>
<td>Predicted Class (Right Region)</td>
<td>29</td>
</tr>
<tr>
<td>Patient</td>
<td>7</td>
</tr>
<tr>
<td>(Left Region)</td>
<td>30</td>
</tr>
<tr>
<td>Patient</td>
<td>6</td>
</tr>
</tbody>
</table>

**Discussion**

The chronic airflow limitation of COPD are caused by a mixture of small airways disease and parenchymal destruction. Diagnostic imaging depends on the doctor’s subjectivity and is a time consuming task. Thus, a pattern recognition approach to the diagnosis of lung diseases would be helpful. In addition to diagnosis, using a mathematical model for indicating the severity of the disease would be useful for following the treatment procedure.
Three cuts method for identification of COPD