A New Scheme for Evaluation of Air-Trapping in CT Images

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Abstract: Air trapping is an abnormal retention of air that occurs after expiration state in the lungs, observed in all types of bronchiolar and obstructive lung diseases such as chronic obstructive pulmonary disease (COPD), asthma, and bronchiolitis obliterans syndrome. Air trapping is often incidentally diagnosed on computed tomography (CT) scanning but this method needs doctors so it is subjective and depends on their experience. In this paper, we present a novel method for evaluation of air trapping in the lungs for detection of COPD in CT images. The proposed method finds volumetric variations of the lungs from inspiration to expiration. To this end, trachea CT images at full inspiration and expiration are compared and the volumetric variations are used to classify the subjects. In the evaluated cases, the proposed method is able to estimate air trapping in the lungs from CT images without human intervention. This method may assist radiologists to measure and evaluate air trapping for detection of COPD as a computer aided diagnosis (CAD) system.

Keywords: Air-Trapping, COPD, CT, Evaluation and Staging.

1. Introduction

Air trapping is a combination of a loss of alveolar attachments and a loss of elastic recoil that makes it hard to empty the lungs completely [1]. Chronic obstructive pulmonary disease is characterized by airflow limitation that is not fully reversible. It is caused by a mixture of airway obstruction (bronchitis and bronchiolitis) and parenchymal destruction (emphysema) or asthma, the relative contributions of which are variable [2]. This obstruction decreases the rate of airflow through the lungs when a person breathes out. In 1990, a study by the World Bank and the World Health Organization (WHO) ranked COPD 12th as a burden of disease. By 2020, it is estimated that COPD will be ranked 5th in the world and in the US, it is projected to be the third leading cause of death for both males and females [3].

Pulmonary function tests are the primary diagnostic tools for air trapping and COPD after the medical history and physical examination. There are four components to pulmonary function testing: lung volumes; spirometry; ostbronchodilator spirometry; and diffusion capacity. Lung volumes are measured in two ways: gas dilution or body plethysmography [4]. The pulmonary function tests are difficult and time consuming and require physician involvement. Evaluation of radiographic features may provide important diagnostic and prognostic information. In addition, changes in these features over time may be used to evaluate new treatment options and monitor treatment responses [5]. Computed tomography has been the main imaging approach in lung diseases including COPD. With the older CT systems, only axial imaging was feasible but high resolution 1 mm thick slices could be obtained at 1 cm increments to generate detailed images of the lung structure [6].

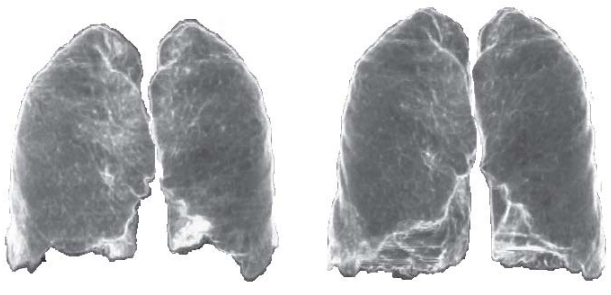

Fig. 1: Anterior view of the lungs, expiration state (left) and inspiration state (right).

Assessment of COPD using CT has a number of potential limitations. Such as, mild COPD may be missed on High Resolution CT (HRCT) and the extent of destruction may be underestimated because localized areas of destruction may be invisible in patients with severe emphysema [7]. In this paper for solving similar limitations of COPD diagnosis, we proposed an automatic method in the base of analyzing correlation of full inspiration and expiration states. Fig. 1 shows anterior view 3D images reconstructed from expiratory (left) and inspiratory (right) MDCT scans (70-year-old man with COPD disease). The presented method finds volumetric changes of the lungs in three dimensions (3D) that may be used to detect and stage air trapping in the COPD. The proposed method is computationally efficient and relieves radiologists from time consuming task of COPD detection. In this paper, after finding the lung parenchyma at full inspiration and expiration, the differences between these two conditions are quantified in three dimensions. The distribution of the resulting feature is then estimated using training data of normal subjects and COPD patients. These distributions are used to define a Bayesian classifier to detect COPD. In addition, discrimination powers of the features are evaluated using statistical t-tests.

2. Lung Extraction

Success of this method depends on accurate segmentation of the lungs. In recent years, computer assisted segmentation of pulmonary CT images has been done through semi-automatic and automatic techniques. The number of segmentation algorithms found in the literature is very high [8]. To segment the lungs and extract appropriate ROI's, we used snakes or active contours. The active contour models works based on minimizing an energy function consisting of an external force and an internal force. The external force is defined from the image data and the internal force is calculated from the curvature of the contour [9] that starts from an initial contour [10]. Fig. 2 shows a transverse CT slice from a healthy subject at the inspiration state and the result of lung extraction.

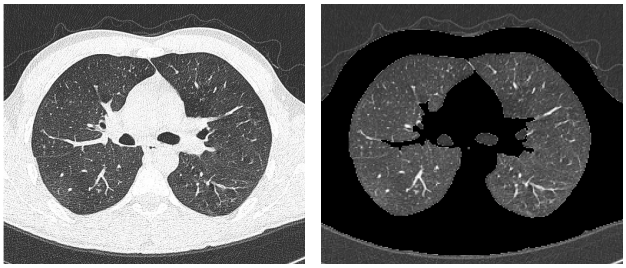

Fig.2: A transverse CT slice (Left), the result of lung extraction (Right).

3. Volume changes

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, especially when there is predominantly emphysema [11], [12] so the volumetric variation is decreased in COPD. In this step changes in the total lung volume in three dimensions are evaluated. For this end, the white pixels in each cut are calculated to find the volume in each state of respiration. To remove the effects of age, height, and sex, a normalized value can be used. To normalize, we used the inspiration area as a reference.

The thorax CT image sets were acquired at the Noor Medical Imaging Center, Tehran, Iran using a SIEMENS High Resolution CT scanner (Sensation 64) from twelve patients and twelve normal subjects. The voxel size was 1×1×3 mm. To reduce computation time, one cut in every 17 cuts is used. Fig. 3 shows the lung parenchyma at inspiration and Fig. 4 shows the lung parenchyma at expiration for a 22 years old healthy female subject. The result of this step is shown in table 1. For finding the relationship of volume changes of full inspiratory and expiratory states with air trapping in COPD patients; we used a set of data samples with associated labels. Our samples are labelled by radiologist doctors.

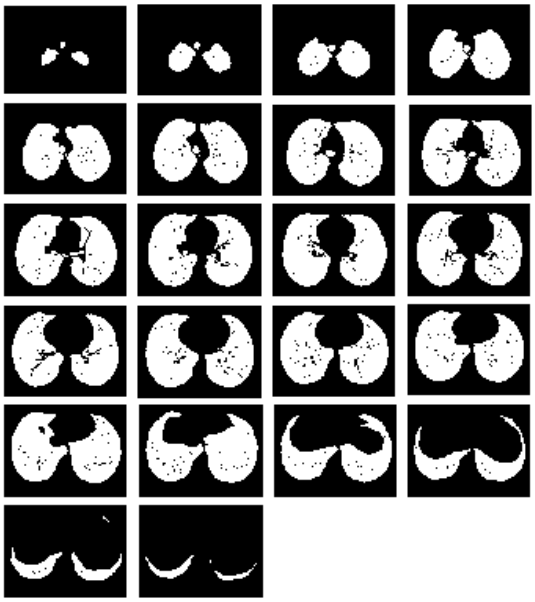

Fig.3: Lung parenchyma (full inspiration state).

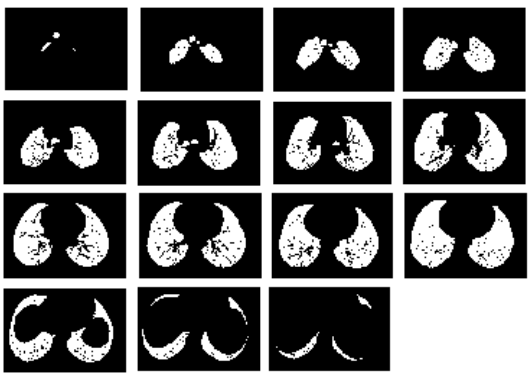

Fig.4: Lung parenchyma (full expiration state).

Table 1: volume changes in data set.

Case Number	Doctor Diagnosis		Age	Sex		Volume Variation
	Normal	Patient		M	F	
1	*		43		*	0.450
2	*		22		*	0.460
3	*		27	*		0.278
4	*		44	*		0.307
5	*		43		*	0.493
6	*		39	*		0.472
7	*		48	*		0.391
8	*		53	*		0.485
9	*		45	*		0.363
10	*		44	*		0.325
11	*		38	*		0.478
12	*		49	*		0.443
13		*	40	*		0.035
14		*	81		*	0.085
15		*	70	*		0.273
16		*	42		*	0.347
17		*	74	*		0.362
18		*	48	*		0.357
19		*	77		*	0.073
20		*	88		*	0.050
21		*	47	*		0.251
22		*	66		*	0.213
23		*	75		*	0.219
24		*	49	*		0.114

4. Classification

In practice, a radiologist may not be able to recognize small volumetric variations reliably from the CT images. Our purpose is to develop an automatic method to reduce labor-intensive procedures [13]. Bayesian decision theory is a fundamental approach based on quantifying the tradeoffs between various classification decisions and the costs that accompany such decisions [14]. Our problem is a supervised classification. We have a set of data samples with associated labels, the class types. These are used as samples in the Bayes classifier design. We have two classes, ω_1 and ω_2 and the Gaussian distribution assumption is used. The goal is to minimize the probability of making an error and there is no information regarding an object other than the class probability distribution. The Bayes rule for minimum error classification is:

$$l_r(x) = \frac{p(x|\omega_1)}{p(x|\omega_2)} \rangle \frac{p(\omega_2)}{p(\omega_1)} \Rightarrow x \in class\,\omega_1 \qquad (1)$$

Where $p(x|\omega_1)$ is the class-conditional density function of class 1 and $p(\omega_1)$ is the a priori probability. The function $l_r(x)$ is the likelihood ratio. The Bayes decision threshold for the volume variation is 0.310 as shown in Fig. 5. The severity of disease can be indicated by Euclidean distance from the hard threshold.

We used t-test to assess whether the means of the two groups of normal subjects and patients are statistically different. The formula for the t-test is a ratio as described in Equation (2). The numerator is the difference between the two means or averages. The denominator is a measure of the dispersion of the scores called the standard error of the difference.

$$t - value = \frac{mean(class1) - mean(class2)}{\sqrt{\frac{variance1}{number1} + \frac{variance2}{number2}}} \qquad (2)$$

In case of unequal variance, the t-test requires the approximation of the degrees of freedom. The number of degrees of freedom is the number of values in the final calculation of a statistic that are free to vary [15]. Among several approximation methods, Satterthwaite's approximation is commonly used. Table 2 shows the result of t-test.

Table 2: Discrimination power of the volumetric variation for classification is shown with the t-test result.

	t-test Value	Degrees of Freedom	p-value	Different between Means
Volume variation	5.1078	18.3338	3.480e-005	Yes

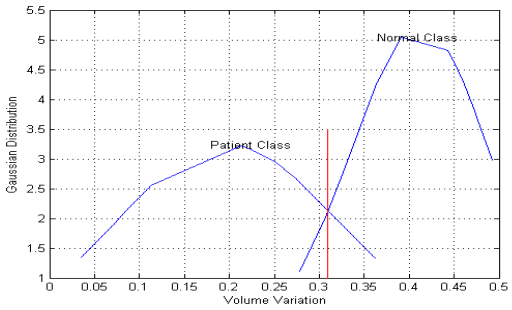

Fig.5: Gaussian distribution of the lung volumetric variation and the hard threshold of discrimination.

5. Conclusion

Hyperinflation of the lungs due to air trapping is a significant cause of breathlessness in COPD [16]. While there is no cure for that and the lung damage that results in this disease cannot be reversed, it is very important to diagnose as early as possible. Without using image analysis results, radiologists are limited in their sensitivity, specificity, and diagnostic accuracy. Due to many parenchymal structures, it is sometimes extremely difficult to decide whether or not a HRCT is abnormal. A pattern recognition approach to the diagnosis of air trapping can be helpful. In addition, a computerized method is needed to monitor the success or failure of treatment. Hyperinflation of the lungs due to air trapping is a significant symptom of COPD, which occurs largely as a result of airflow limitation. In this paper, we presented an automatic 3D method for identification of air trapping in the lungs in COPD. This method finds the variation of the lung parenchyma at full inspiration and expiration in CT images. The proposed method can be used for scoring severity of air-trapping in the lung, in addition to the diagnosis and treatment evaluation as well as screening individuals at the risk of COPD.

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References

[1] Air-trapping. http://breathinstephen.com/category/asthma/asthma-symptoms-asthma-medical-asthma-medical/, Retrieved on October 12, 2010.

[2] J. Ley-Zaporozhan, H. U. Kauczor, and S. Ley, "Magnetic Resonance Imaging of Pulmonary Diseases," Imaging Decisions, Vol. 13, pp.2-10, spring 2009.

[3] COPD Statistical Information. http://www.copd-international.com/library/statistics.html/, Retrieved on July 11, 2010.

[4] Diagnosis of Chronic Obstructive Pulmonary Diseases. http://www.pulmonologychannel.com/copd/, Retrieved on July 10, 2010.

[5] K. R. Flaherty, "Idiopathic Pulmonary Fibrosis: The Importance of Qualitative and Quantitative Phenotyping," Imaging Decisions, Vol. 13, pp. 18-23, spring 2009.

[6] E. J. R. Van Beek, and E. A. Hoffman, "Imaging in COPD," Imaging Decisions. Vol. 13, pp.11-17, spring 2009.

[7] S. Hu, E. A. Hoffman, and J. M. Reinhardt, "Automatic Lung Segmentation for Accurate Quantitation of Volumetric X-Ray CT Images," IEEE Trans Med Imaging, Vol. 20, No. 6, June 2001.

[8] S. Lakare, "3D Segmentation Techniques for Medical volumes," Technical Report, State University of New Yourk, December 2000.

[9] Ch. Seokyoon, and K. Changsoo, "Automatic Initialization Active Contour Model for the Segmentation of the Cheast Wall on Chest CT," Healthc Inform Rev., Vol6. 1, pp. 36-45, March. 2010.

[10] S. Lobregt, and M. A. Viergever, "A Discrete Dynamic Contour Model," IEEE Trans Med Imaging, Vol 14, pp. 12-24, 1995.

[11] K. Kuwano, K. Matsuba, and T. Ikeda, "The Diagnosis of Mild Emphysema: Correlation of Computed Tomography and Pathology Scores," Am Rev Respir Dis, Vol. 141, pp. 169-178, 1990.

[12] R. A. Stockley, S. I. Rennard, K. Rabe, and B. Celli, "COPD: Clinical Presentation and Evaluation, in Chronic Obstructive Pulmonary Disease," Blackwell Publishing Ltd, Oxford, UK, 2008, ch15.

[13] R. O. Duda, P. E Hart, and D. G. Stork, "Pattern Classification," 2nd ed., Wiley-Interscience, chapter2, 2001, p. 3.

[14] A. R. Webb, "Statistical Pattern Recognition," 2nd ed., John Wiley and Sons Ltd. , 2002, p.5.

[15] H. M. Park, "Comparing Group Means: T-tests and One-way ANOVA Using Stata, SAS, R, and SPSS," Working Paper. UITC Center of Statistical and Mathematical Computing, Indiana University, 2009.

[16] D. Price, D. Freeman, A. Kaplan *et al*., "The role of hyperinflation and its pharmacological management," Primary Care Respiratory Journal, Vol. 15, p. 128, 2006.