Three Cuts Method for Identification of COPD

Mohammad-Parsa Hosseini[1,2], Hamid Soltanian-Zadeh[2,3], and Shahram Akhlaghpoor[4]

[1] *Department of Electrical and Computer Engineering, Wayne State University, Detroit, MI, USA*

[2] *Medical Image Analysis Laboratory, Radiology and Research Administration Departments, Henry Ford Health System, Detroit, MI, USA*

[3] *Control and Intelligent Processing Center of Excellence, School of Electrical and Computer Engineering, University of Tehran, Tehran, Iran*

[4] *Department of Radiology, Sina Hospital, Tehran University of Medical Sciences, Tehran, Iran*

Received: 2 Nov. 2011; Received in revised form: 15 Sep. 2012; Accepted: 26 Oct. 2012

Abstract- Two main forms of COPD (Chronic Obstructive Pulmonary Disease) refer to a group of 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 would be helpful for evaluation of treatment effects and early diagnosing is presented in this paper. This method has five main steps. Firstly, corresponding positions of lungs in inspiration and expiration are found based on anatomical structures. Secondly, lung regions are segmented from the CT images by active contours. Next, the left and right lungs are separated using a sequence of morphological operations. Then, parenchyma variations of three main cuts which selected by a feed-forward neural network are found based on the inspiratory and expiratory states. Finally, a pattern classifier is used to decide about the disease and its severity. Twenty patients with air-trapping problems and twelve normal adults were enrolled in this study. Based on the results, a mathematical model was developed to relate variations of lung volumes to severity of disease. The sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV) and the accuracy of our method for right regions were %81.6, %80.5, %87.5, %72.5 and %81.3 respectively. And these parameters for left regions were %90, %83.3, %90, %83.3 and %87.5 respectively. The proposed method may assist radiologists in detection of Asthma and COPD as a computer aided diagnosis (CAD) system.

Acta Medica Iranica, 2013; 51(11): 771-778.

Keywords: Air trapping; Chronic Obstructive Pulmonary Disease (COPD); Computer Aided Diagnosis (CAD); Neural Network; Pattern Recognition; 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 that includes emphysema, chronic bronchitis, chronic bronchitis, and small airway disease (2). COPD is the fourth leading cause of death in the United States 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 medical history and physical examination. Computed tomography (CT) has been the main imaging approach for lung diseases including COPD and Asthma may allows 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 test have been shown in many studies. In (4), a comparison between findings of inspiratory and expiratory HRCT and pulmonary function tests is done. Previous works as well as physicians' perceptions suggest that analyzing correlation of the inspiration and expiration states would be helpful for evaluation of severity of asthma and COPD. Reference (5) reports that

Corresponding Author: Mohammad-Parsa Hosseini
Department of Electrical and Computer Engineering, Wayne State University, Detroit, MI, USA
Medical Image Analysis Lab., Radiology and Research Admistration Departments, Henry Ford Health System, Detroit, MI, USA
Tel: +131 33200462, Fax: +131 38744494, E-mail: parsa.hosseini@wayne.edu

measurements of lung attenuation in patients with less severe COPD can be well reflected at the inspiration state while for patients with severe COPD expiration indicates better results in comparison with the inspiration. Paired inspiratory and expiratory volumetric thin-slice CT scan was used for emphysema analysis by Zaporozhan, *et al.* (6). Some volumetric analysis to detect and stage of COPD have been presented by Hosseini, *et al.* (7-10). In these papers some idea suggested for designing a computer aided diagnosis systems for COPD detection using volumetric variations of lung body. In (11) have been shown that 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 evaluation of air-trapping in lungs for detection and scoring severity of asthma and COPD using CT images. Severe effects of asthma and COPD may include loss of elasticity of the lungs due to air trapping. COPD reduces maximum expiratory flow by decreasing the elastic recoil force available to drive air out of the lungs. In this study, we score parenchyma variations of the lungs in CT images as they reflect elasticity and air-trapping. For this purpose, three important cuts of the lungs that indicate the disease more than other cuts are used. A neural network was used for finding these cuts. Radiologists diagnose COPD in CT images visually; this is difficult, time consuming, and subject to human errors. The proposed method detects and scores asthma and COPD severity automatically. Because of the large number of images generated by CT, developing computer-aided diagnosis (CAD) systems that assist radiologists in the detection of COPD would be helpful. We designed such a CAD system to assess asthma and COPD in the CT images of the lungs.

Materials and Methods

Subjects

The thorax CT image sets 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 patients were selected among those who were visited at the radiology and pulmonary clinic of Noor Medical Imaging Center (Tehran, Iran). The patient group in this study consisted from subjects who had air trapping (asthma or COPD) according to its accepted definition. 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 1×1×3 mm. Scanning voltage and current was 120 kV and 254 mA. In each case, 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 16×1.25 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. Written informed consents were also obtained from all subjects. All aspects of the study were conducted according to the declaration of Helsinki.

Methods

The greater prominence 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 asthma or COPD disease progression. As shown in Figure 1, our method consists of five main steps: a matching between inspiration and expiration slices; an extraction step to identify the lungs; a separation step to separate the right and left lungs; a parenchyma variation finder for finding and comparing elastic recoil and a pattern classifier for categorizing the subjects into normal subjects and patients.

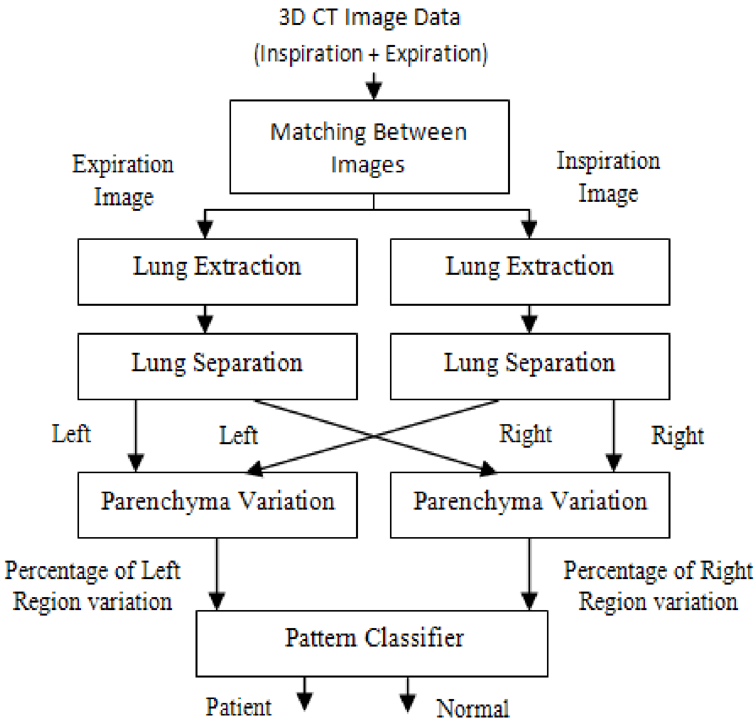

Figure 1. Diagram of the 3-cuts method.

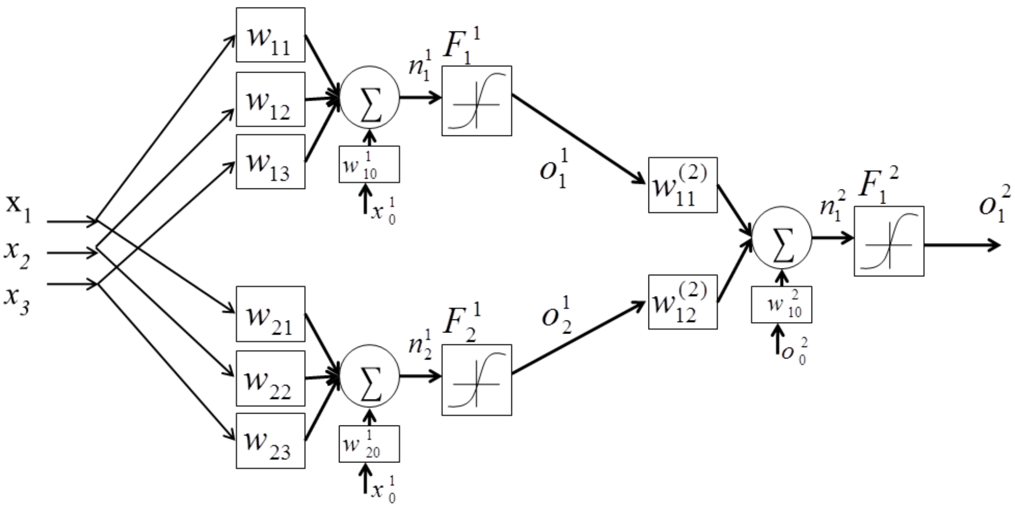

Figure 2. Artificial neural network which used for finding significant cuts.

Matching between images

Each frame shows particular anatomical structures. Spatial properties of organs are typically dependent upon, and described relative to, one another. We should analyze the same positions of the same patient in the inspiratory and expiratory states. When we evaluate all cuts, our method is fully automatic and does not need to find the corresponding images of the inspiratory and expiratory states (12). However, this increases accuracy as well as the computation time. A feed-forward neural network was used for finding significant cuts as shown in Figure 2. Different cuts of the case group and some other accepted subjects were assigned as input values of the neural network. Base on the output and medical surveys, three cuts of lung which indicate disease and air-trapping more than others were selected for parenchyma variations. These three cuts are upper, middle, and lower parts of the lungs have most significant impact on our test. So, we used only these cuts for reducing the time of computation. In addition, if this test accepts as a regular test, it only needs to scan patients in these three cuts so the radiation dose and exposure time of the CT scans significantly reduced. All of the subjects were imaged for their routine diagnosis process and they were not exposed to additional radiation for this research. So, we should extract and identify the corresponding cuts from others. For finding the corresponding images, we use anatomical structures (13) such as aortic arch and carina trachea. 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).

Lung extraction

Success of our method depends on accurate segmentation of the lungs. Many segmentation algorithms are proposed in the literature. Various lung segmentation methods are proposed for specific applications. In recent years, computer assisted segmentation of pulmonary CT images has 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 and are extensively used in the medical image processing applications. A modified active contours without edges which first time proposed by Chan *et al.* (14) is used in this paper for lung parenchyma extraction 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.

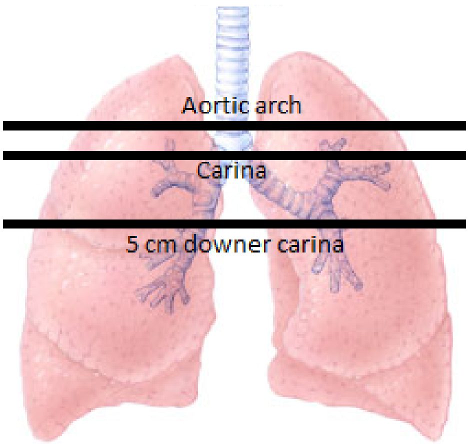

Figure 3. Slices used for the 3 cuts method.

Lung separation

Because COPD may only exist in one of the lungs, we assessed 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 this purpose, we use a combination of labeling connected components in 2D binary images and morphological operations. Connected components are useful for all cuts 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. Like (16,17), a conditional dilation is then used to restore the approximate original boundary shape, without reconnecting the two lungs again. Erosion shrinks an image by selecting the minimum value of all pixels in the neighborhood of the input pixel. On the other hand, dilation expands an image by selecting the maximum value. The structuring element defines the neighborhood of the pixel of interest. We use four connected (diamond-shaped) binary structuring elements; the results are shown in Figure 5.

Parenchyma variations

Resistance of small conducting airway 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 asthma and COPD, airflow and variation of areas of the lungs between inspiration and expiration states are less than the normal state. The percentage of lung area variations in inspiration and expiration stages are used to indicate the lung elasticity in this step. For this purpose, the variation in three important cuts which were found in the first step and show air trapping more than other cuts are evaluated. This elasticity percentage shows the air trapping in the lungs and is used to diagnose asthma and COPD. To have the same form of variation, the effects of age, height, weight, and sex should be removed. To this end, we use the inspiration area as a reference. So, the normalized scores for parenchyma variation in the separated lungs are found in this step. Figure 6 shows the parenchyma variation for separated lungs between inspiration and expiration states at the carina cut.

Pattern classifier

A Bayes pattern classifier for categorizing the results into two classes of normal and patient subjects is used as the last step of our proposed method. This classification is about assigning labels to subjects which are described by one or a set of measurements called features (19). Our feature is the parenchyma variation that shows the air-trapping in each cut. Accurate diagnosis depends on accurate classification of our feature to one of the normal or patient classes. The assumption of Gaussian distribution is used for the data set. The Bayes rule minimized the probability of making an error to assign datasets to one of the two classes.

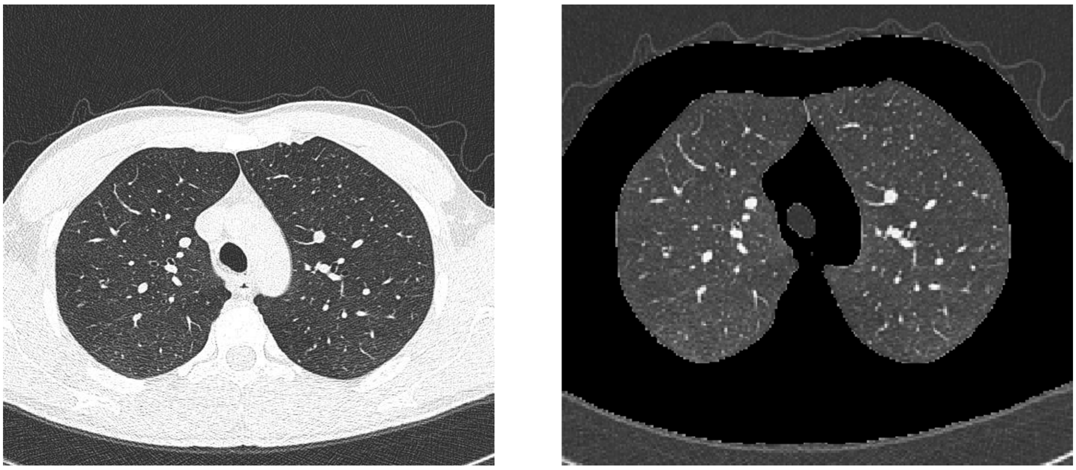

Figure 4. A transverse CT slice of a healthy subject (left) and its segmentation result (right) at approximately carina cut.

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

Figure 6. Left: Comparing the parenchyma variation in the left lung. Right: The result for the right lung.

Statistical analysis

We used t-test to assess whether the means of the two groups of the normal subjects and the patients are statistically different or not. Table 1 shows the mean and standard deviation (SD) of the each class. Table 2 shows the results of the 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 and SPSS 10.0 statistical programs. As shown in the 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 subject in three curs. Figure 7 shows the normal distribution for the data sets of the 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 used for all subjects in labeled data set which were done by expert radiologists and the proportion of misclassified objects is found. The errors of applying the Bayesian classifier are given in Table 3 as a misclassification matrix or confusion matrix.

The Bayes decision threshold for the right and left lungs are found %31.16 and %30.05, respectively (Figure 7). It should be noted that other thresholds can be used in the Bayes decision rule to minimize the Reject Option, Risk, or Neyman–Pearson criterion. The sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV) and the accuracy of our method for right regions were %81.6, %80.5, %87.5, %72.5 and %81.3 respectively. And these parameters for left regions 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. Figure 8 shows strength, shape, and presence of outliers.

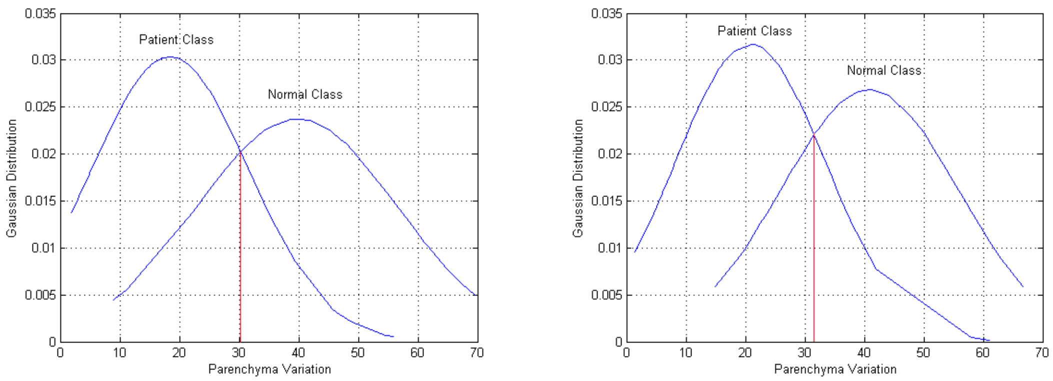

Figure 7. Gaussian distribution of the percentage parenchyma variation for left (Left) and right Lungs (Right).

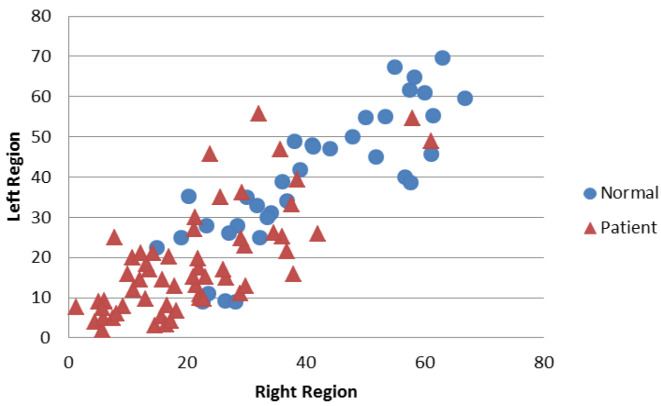

Figure 8. The relationship between the right and left lung parenchyma variation in the normal and patient classes.

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

Group	Sample Size	Left Lung Mean	Left Lung SD	Right Lung Mean	Right Lung SD
Normal	12	39.76	16.81	40.87	14.87
Patient	20	18.44	13.14	20.83	12.59

Table 2. The t-test results.

Region	t-test Value	Degrees of Freedom	*P*-value	Difference of the Means
Left	3.81	86	2.6e-004	yes
Right	3.38	87	0.001	yes

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

Confusion Matrix		True class Normal	True class Patient
Predicted Class (Right Region)	Normal	29	11
	Patient	7	49
Predicted Class (Left Region)	Normal	30	6
	Patient	6	54

Discussion

The chronic airflow limitation characteristics of COPD are caused by a mixture of small airways disease and parenchymal destruction. Diagnostic imaging depends on doctor's subjectivity and is time consuming. Thus, a pattern recognition approach for their diagnosis would be helpful. Moreover, using this mathematical model to indicate severity of the disease would be adequate for following the treatment procedure.

Our study is different from previous studies in materials and methods. Hosseini *et al.* assessed lung volumetric variation for 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 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 problem of that system. In this paper the problems of previous works resolved and the efficiency of proposed CAD system improved. In addition, the proposed method is able to estimate air trapping in the lungs from CT images without human intervention.

References

1. World Health Organization. Global surveillance, prevention and control of chronic respiratory diseases: a comprehensive approach, 2007.
2. Kasper DL, Braunwald E et al. Disorders of respiratory system, in Harrison's principls of internal medicine, 16th ed., McGraw-Hill, 2005;2:1547.
3. COPD Statistical Information. http://www.copd-international.com/, Retrieved on July 11,2010.
4. Terasaki H, Fujimoto K, Müller NL, Sadohara J, Uchida1 M, Koga T, Aizawa H, Hayabuchi N. Pulmonary sarcoidosis: comparison of findings of inspiratory and expiratory high-resolution CT and pulmonary function tests between smokers and nonsmokers. AJR 2005;185:333-8.
5. Akira M, Toyokawa K, Inoue Y, Arai T. Quantitative CT in chronic obstructive pulmonary disease: Inspiratory and Expiratory Assessment. AJR 2009;192:267-72.
6. Zaporozhan J, Ley S, Eberhardt R, Weinheimer O. Paired Inspiratory/Expiratory Volumetric Thin-Slice CT Scan for Emphysema Analysis Comparison of Different. Chest 2005;128:3212-20.
7. Hosseini MP, Soltanian-Zadeh H, Akhlaghpoor SH. A Novel Method for Identification of COPD in Inspiratory and Expiratory States of CT Images. Proceeding of the First Middle East Conference on Biomedical Engineering, Sharjah, U.A.E., 2011;22-5.

8. Hosseini MP, Soltanian-Zadeh H, Akhlaghpoor SH, Behrad A. A new scheme for evaluation of air-trapping in CT images. Proceeding of the 6th Iranian Conference on Machine Vision & Image Processing, Isfahan, Iran, 2010.
9. Hosseini MP, Soltanian-Zadeh H, Akhlaghpoor SH. Assessing Lung Volumetric Variation to Detect and Stage COPD. Proceeding of the First Middle East Conference on Biomedical Engineering, Sharjah, U.A.E. 2011;22-5.
10. Hosseini MP, Soltanian-Zadeh H, and Akhlaghpoor SH. Computerized Processing and Analysis of CT Images for Developing a New Criterion in COPD Diagnosis. J Isfahan Med School. Special Issue. Biomedical Engineering 2012;29(174):1-7.
11. Fain SB, Peterson ET, Sorkness RL, Wenzel S, Castro M, Busse WW. Severe asthma research program phenotyping and quantification of severe Asthma. Imaging Decisions J 2009;13(1):18-24.
12. Hosseini MP, Soltanian-Zadeh H, Akhlaghpoor SH. Detection and Severity Scoring of Chronic Obstructive Pulmonary Disease Using Volumetric Analysis of Lung CT Images. Iran J Radiol. 2012;9(1):22-7. DOI: 10.5812/iranjradiol.6759.
13. Brown MS, McNitt-Gray MF, Mankovich NJ, Nicholas J, Goldin JG. Method for segmenting chest CT image data using an anatomical model: Preliminary results, IEEE Trans. Med. Imag 1997;16:828-39.
14. Chan TF, Vese LA. Active Contours Without Edges. IEEE Transactions on Image Processing, 10(2):266-77.
15. Hosseini MP, Soltanian-Zadeh H, Akhlaghpoor SH, Jalali A, Bakhshayesh Karam M, “Designing a New CAD System for Pulmonary Nodule Detection in High Resolation Compuetd Tomography (HRCT) Images. TUMJ 2012; 70(4):250-6.
16. Shiying H, Hoffman EA, Reinhardt JM. Automatic lung segmentation for accurate quantitation of volumetric X-ray CT images. IEEE Tran. Medical Imaging 2001;20(6):490-8.
17. Hu S, Hoffman EA, Reinhardt JM, “Automatic Lung Segmentation for Accurate Quantitation of Volumetric X-ray CT Images. IEEE Trans Med Imaging 2001;20(6):490-8.
18. Matsuoka S, Kurihara Y, Yagihashi K, Hoshino M, Nakajima Y. Airway dimensions at inspiratory and expiratory multisection CT in chronic obstructive pulmonary disease: correlation with airflow limitation. Radiology 2008;248(3):1042-9.
19. Kuncheva LI. Combining pattern classifier: Methods and Algorithm. John Wiley Inc., Canada 2005; p.8.
20. Kobayashi R, Tanaka T, Nakamura H, Shirahanta T, et al, Algorithm of pulmonary emphysema analysis using comparing with expiratory and inspiratory state of CT images in Proc. SICE, 2008;3105-9.
21. Hosseini MP, Soltanian-Zadeh H, and Akhlaghpoor SH. CAD system for the evaluation of chronic obstructive pulmonary disease on CT Images. TUMJ 2011;68(12):718-25.