An application to pulmonary emphysema classification based on model of texton learning by sparse representation

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ABSTRACT

We aim at using a new texton based texture classification method in the classification of pulmonary emphysema in computed tomography (CT) images of the lungs. Different from conventional computer-aided diagnosis (CAD) pulmonary emphysema classification methods, in this paper, firstly, the dictionary of texton is learned via applying sparse representation(SR) to image patches in the training dataset. Then the SR coefficients of the test images over the dictionary are used to construct the histograms for texture presentations. Finally, classification is performed by using a nearest neighbor classifier with a histogram dissimilarity measure as distance. The proposed approach is tested on 3840 annotated regions of interest consisting of normal tissue and mild, moderate and severe pulmonary emphysema of three subtypes. The performance of the proposed system, with an accuracy of about 88%, is comparably higher than state of the art method based on the basic rotation invariant local binary pattern histograms and the texture classification method based on texton learning by *k*-means, which performs almost the best among other approaches in the literature.

Keywords: emphysema, computed tomography (CT), texture classification, texton, sparse representation, dictionary learning

1. INTRODUCTION

Chronic obstructive pulmonary disease (COPD) is a disease of pulmonary system and is a growing health problem worldwide. Coughing up mucus is an early sign of COPD. The term chronic obstructive pulmonary disease or COPD is often used to describe patients who have chronic and largely irreversible airways obstruction, most commonly associated with some combination of emphysema and chronic bronchitis [1]. By 2030, COPD is predicted to be the 3rd leading cause of death worldwide. Emphysema is one of an important kind of COPD. It can be characterized by gradual loss of lung tissue, and diagnosed with computed tomography (CT) imaging.

The three described morphological types of emphysema are centrilobular, panlobular and paraseptal. Centrilobular emphysema (CLE), also termed centriacinar emphysema, begins in the respiratory bronchioles and spreads peripherally. This form is associated with long-standing cigarette smoking and predominantly involves the upper half of the lungs. Panlobular emphysema (PLE) destroys the entire alveolus uniformly and is predominant in the lower half of the lungs. Panlobular emphysema generally is observed in patients with homozygous alpha1-antitrypsin (AAT) deficiency, which is suffer from the aforementioned genetic disease. Paraseptal emphysema (PSE), also known as distal acinar emphysema, is characterized by involvement of the distal part of the secondary lobule and is therefore most striking in a subpleural location. Areas of subpleural paraseptal emphysema often have thin and visible walls. They often correspond to interlobular septa. As with centrilobular emphysema, some fibrosis may be presented. Even mild paraseptal emphysema is easily detected by high–resolution computed tomography (HRCT).

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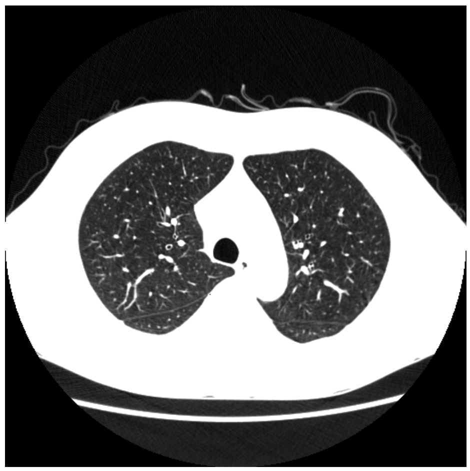
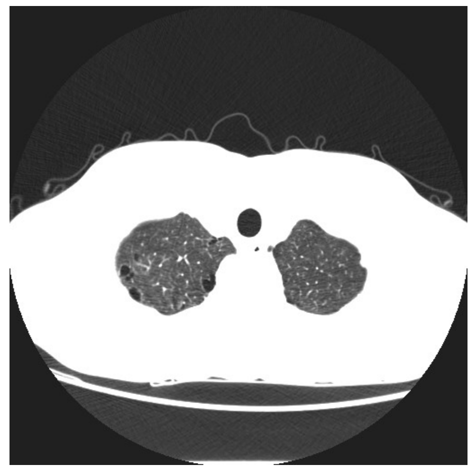
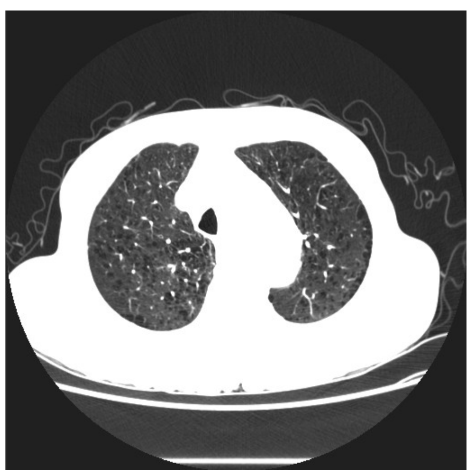
HRCT can provide an accurate assessment of lung tissue patterns [2]. Three-dimensional (3D) image of the pulmonary volumes produced by HRCT can avoid the superposition of anatomic structures, and is suitable for the assessment of lung tissue texture. Examples of emphysema patterns in HRCT slice and normal tissue are shown in Figure 1. The extracted region of interest (ROI) emphysema patterns in HRCT slice and normal tissue are shown in Figure 2. On HRCT, emphysema is characterized by the presence of areas of abnormally low attenuation, which can be easily distinguished with surrounding normal lung parenchyma if sufficiently low window means are used [3-5]. In most instances, focal areas of emphysema can be easily distinguished from lung cysts or honeycombing; focal areas of emphysema often lack distinct walls [3,4,6].



(a) Normal tissue



(b) PSE



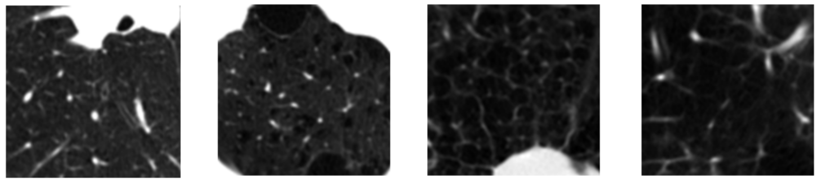
(c) CLE

(d) PLE

Figure 1. Examples of emphysema patterns in CT slice of size 512×512 in three classes and normal tissue. The examples of CT slices where the leading emphysema pattern was determined by an experienced chest radiologist.

Computerized diagnosis and quantification of emphysema are very important. Commonly emphysema classification and quantification approaches in CT are mostly based on the histogram of CT attenuation values [7]. The quantitative measures of the degree of emphysema is derived from this histogram. The most common measure is the relative area of emphysema (RA), which measures the relative amount of lung parenchyma pixels that have attenuation values below a certain threshold [8]. Another way to objectively characterize the emphysema morphology is to describe the local image structure using texture analysis techniques. Uppaluri et al. developed a adaptive multiple feature method (AMFM) for examining the lung parenchyma from HRCT scans [9]. The AMFM is a texture-based method that combines statistical texture measures with a fractal measure. 17 measures of texture were used, including the grey level distribution measures, run-length measures, co-occurrence matrix measures, and a geometric fractal dimension (GFD). This idea is followed by classification method of regions of interest (ROIs) for various lung disease patterns by using different texture features

[10-12]. In some methods, shape, or geometric, measures are also included in conjunction with the texture features [13-15].



(a) Normal (b) PSE (c)CLE (d)PLE

Figure 2. Examples of region of interest (ROI) emphysema patterns of size 100×100 in three classes and normal tissue. The examples are from CT slices where the leading emphysema pattern was determined by an experienced chest radiologist. Black is missing lung tissue due to emphysema, White is outside the body. Gray is lung tissue.

Recently, texture classification method based on local binary patterns (LBP) and texton learning by *k*-means are introduced for classification and quantification of COPD [16-18]. Small-sized local operators, such as LBP and patch representation in texton-based approaches yield excellent texture classification performance on standard texture databases [19]. Small-sized local operators are especially desirable in situations where the region of interest (ROI) is rather small, which is often the case in texture analysis in medical imaging, where pathology can be localized in small areas. While, in these methods, only moderate and severe emphysema subjects are selected. However, the importance of obtaining an early diagnosis of emphysema cannot be overemphasized. So the classification method should be robust and sensitive in different stages of emphysema diagnosis. In this paper, we present to use a new texture classification method based on texton learning by sparse representation [20] in the classification of emphysema. This method is inspired by the great success of l_1-norm minimization based sparse representation (SR). The dictionary of texton is learned via applying SR to image patches in the training dataset. The SR coefficients of the test images over the dictionary are used to construct the histograms for texture classification. The test subjects, including mild, moderate and severe emphysema, are used to testify and compare the effectiveness and robustness of the proposed method, the texture classification method based on the basic rotation invariant LBP histograms [16] and the texture classification method based on texton learning by *k*-means, which performs almost the best among other approaches in the literature.

2. METHOD

2.1 Texton learning based on dictionary learning via sparse representation

In traditional texton based texture classification methods, the codebook of texton are usually constructed using *k*-means. The *k*-means clustering method is based on the l_2-norm Euclidean distance so that the elements of a cluster will have a ball-like distribution. The learned *k* ball-like clusters may not be able to characterize reasonably well the intrinsic feature space of the texture images. Recently, there is a growing interest in the use of sparse representations for signals. Sparsity in an overcomplete dictionary is the basis for all kinds of highly effective signal and image presentations. It bases on the suggestion that natural signals can be efficiently represented as linear combinations of prespecified atom signals with linear sparse coefficients. Formally, if x is a column signal and D is the dictionary (each column is a atom signal), this sparsest representations is the solution of

$$\hat{\gamma} = \operatorname{Arg}\min_{\gamma} \|\gamma\|_0 \text{ Subject to } \|x - D\gamma\|_2^2 \leq \varepsilon, \tag{1}$$

where γ is the sparse representation of x, ε is the error tolerance, and $\|\cdot\|_0$ is the l_0 -norm which counts the non-zero coefficients. This is a NP-hard problem, therefore it is commonly approximated substituting the l_1-norm in Equation (2).

$$\hat{\gamma} = \operatorname{Arg}\min_{\gamma} \|\gamma\|_1 \text{ Subject to } \|x - D\gamma\|_2^2 \leq \varepsilon, \tag{2}$$

Inspired by the great success of l_1-norm minimization based sparse representation (SR), new patch based sparse texton learning method for texture classification is developed [20].

2.2 The proposed method

The proposed method mainly inlcudes four stages: 1) ROI image pre-processing; 2) construction of a dictionary of textons via sparse representation; 3) learn texton histograms from the training set; and 4) ROI image classification. The details of the proposed method are as follows.

1. Before texton learning, all training texture ROI images are normalized to have zero mean and unit standard deviation. The normalization offers certain amount of invariance to the different illumination. A square neighborhood around each pixel in the image is cropped and is stretched to a vector.

2. *Texton learning on sparse representation*

a) In the texton learning stage, sparse representation is selected in this paper [20]. For each type of ROIs, x is the patch vector at a position in a training sample image of this type. The dictionary of textons, denoted by $\mathrm{D}=[d_1,d_2,...,d_k]$, can be learned from the constructed training dataset x, where $d_j, j=1,2,\cdots,k$ is one of the k textons.

b) Then an overcomplete dictionary of texton is learned by optimizing D and γ of the function below using a form of l_1-penalized least-squares

$$\hat{\gamma} = \mathrm{Arg}\min_{\gamma} \|\gamma\|_1 \text{ Subject to } \|x - D\gamma\|_2^2 \leq \varepsilon, \tag{2}$$

where $\gamma=[\alpha_1,\alpha_2,...,\alpha_n]$ is the SR objective function.

3. With this learned dictionary of texton, a feature histogram of a ROI image is formed by comparing each patch representation in that ROI image with all textons in the dictionary using a similarity measure to find the closest match and updating the corresponding histogram bin. Or the feature histogram of an image can be formed as a fractional histogram by summing all the vectors of γ [20].

4. Finally, a ROI image can be classified into the corresponding class by a classifier using the feature histogram.

3. EXPERIMENTS AND RESULTS

3.1 Data preparation

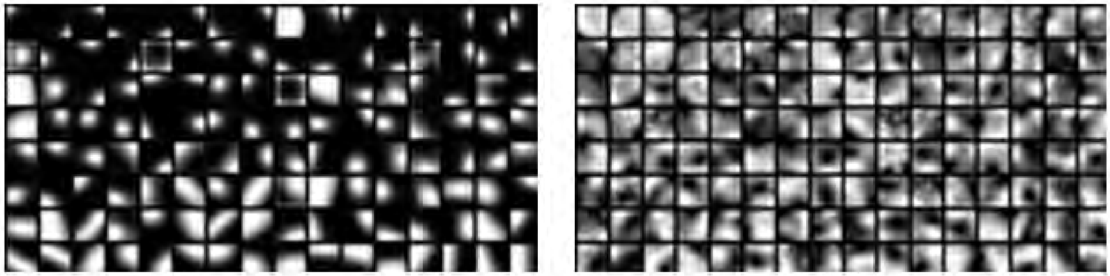
The dictionary of texton is learned via applying SR to image patches in the training dataset. The SR coefficients of the test images over the dictionary are used to construct the histograms for texture classification. The test subjects, including mild, moderate and severe emphysema, are used to testify and compare the effectiveness and robustness of the proposed method, the texture classification method based on the basic rotation invariant LBP histograms [16] and the texture classification method based on texton learning by *k*-means, which performs almost the best among other approaches in the literature.

The proposed scheme was applied to 18 patient cases of non-contrast CT images. Each CT image covers the whole torso region with an isotopic spatial resolution of 0.63 [mm] and a 12 [bits] density resolution. The test images were obtained from 18 different subjects, including 9 healthy subjects and 9 subjects with three subtypes of pulmonary emphysema of different stage. Totally 1984 64×64 region of interests (ROIs) are extracted from the 9 healthy subjects and 1856 64×64 ROIs are extracted from 9 subjects with emphysema.

3.2 Experimental results and Comparison

In this section, we present the results of the proposed method. The comparison results with other methods are also provided. Preliminary results are shown in Table 1 and Table 2 along with the result obtained based on *k*-NN classification framework.

In the experiments, training set was constructed only by 80 ROIs, which account for 4.2% of totally ROIs, for the healthy subjects and subjects with emphysema separately. This training set was used for the texton learning by *k*-means [17] and the texton learning by sparse representation to build 128 textons separately. Patch size of 8×8 are used in the experiments. The compared method 1 and method 2 indicate the texture classification method based on the texton learning by *k*-means and the texture classification method based on the basic local binary pattern (LBP) [16] histograms separately. The texture image is classified to the corresponding texture class by a nearest neighbor classifier in these three methods. Figure 3 shows comparison of the codebook learned by *k*-means and the dictionary learned by sparse representation.



(a) (b)

Figure 3. Comparison of texton codebook learning by *k*-means and the dictionary learned by sparse reprensentation: (a) The constructed codebook using texton size of 8×8 pixels and *k*=128. (b) The learned dictionary using texton size of 8×8 of 128 atoms.

Table 1. The comparison of the average performance for different classification systems on HRCT ROI images of lung with a nearest neighbor classifier.

Texton size	Method	Average Accuracy
8×8	Proposed method	87.8%
8×8	Compared method 1	86.8%
/	Compared method 2	60.1%

Table 2. The comparison between the results obtained from the proposed approach and the results of other techniques on the same data.

		Estimated labels	
Proposed method	True label	Normal tissue	Emphysema
	Normal tissue	1451 (78.1%)	65 (3.3%)
	Emphysema	405 (21.8%)	1919 (96.7%)
		Estimated labels	
Compared method 1	True label	Normal tissue	Emphysema
	Normal tissue	1439 (77.5%)	91 (4.6%)
	Emphysema	417 (22.5%)	1893 (95.6%)
		Estimated labels	
Compared method 2	True label	Normal tissue	Emphysema
	Normal tissue	1268 (68.3%)	943 (47.5%)
	Emphysema	588 (31.7%)	1041 (52.5%)

From Table 1 and Table 2, both the proposed method and the compared method 1 achieve good ROI classification accuracies and high correlations using full feature histograms. While basic rotation invariant LBP based emphysema classification results is not as good as the other two methods. Rotation invariant LBP operators can be considered as fixed textons which are irrespective of the signals. But it is much simpler than texton-based methods since it is lack of training process. The proposed method performs better than the compared method1 due to more accurate texton extraction from the training set. Texton learning by sparse representation can characterize the intrinsic feature space of the texture images better than *k*-means based texton learning method.

4. CONCLUSION

This paper presents a new texture classification method based on texton learning via sparse representation for pulmonary emphysema classification in HRCT images. The dictionary of texton is learned via applying sparse representation (SR) to image patches in the training dataset and the SR coefficients of the test images over the dictionary are used to construct the histograms for texture classification.The dataset includes 3840 annotated ROIs consisting of normal tissue and mild, moderate and severe emphysema of three subtypes, The average performance of 144 experiments of the proposed system, with an accuracy around 88%, is slightly higher and more stable than the compared texture classification methods based on conventional texton learning.

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