Continuous Local Histogram Descriptor For Diagnosis of Bronchiolitis Obliterans

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***Abstract*— Texture feature is an important feature analysis method in computer-aided diagnosis systems for disease diagnosis. However, texture feature itself could not provide an overall description of the diseases. In this paper, we propose Continuous Local Feature (CLH) to diagnose the Bronchiolitis Obliterans (BO) lung diseases in the chest computer tomography images. CLH is based on the continuous combination of histograms of local texture feature, local shape feature, and the brightness feature. Because CLH extracts more information, it has high discriminating power and is able to classify between the BO lung disease and normal lung region effectively. The experimental results in classifying between BO and normal lung region show that CLH achieves 98.15% of average sensitivity whereas Local Binary Patterns and Gray Level Run Length Matrix achieve 73% and 75.8% of average sensitivities, respectively. In the receiver operating curve analysis, CLH archives 0.9 of area under curve (AUC) whereas LBP and GLRLM achieve 0.78 and 0.86 of AUCs.**

Keywords-component; continuous local feature, CAD system, bronchiolitis obliterans, CT images

I. INTRODUCTION

Computed tomography (CT) scans are usually applied to examine the pathological change of the tissues inside the body. However, for examining the pathological change of the tissues, CT scans generate a large number of images. Therefore diagnosing pathological changes using CT image are exhausting for radiologists. Recently, a number of computer-aided detection (CAD) systems [1, 2, 3, 4] have been developed to help the radiologists to diagnose diseases. Thus, using CAD systems to detect lung diseases such as emphysema, honeycombing, and lung cancer has become a significant part in the medical image processing in nowadays [5, 6, 7].

Feature extraction in CAD system is one of the most important steps in recognizing the abnormal regions from the medical image. Texture feature is a fundamental feature for image segmentation [1, 8], classification [8], image retrieval systems [10, 11] etc. In the past decades, texture features such as the gray level difference method (GLDM), the gray level run-length method (GLRLM), and the special gray level dependent method (SGLDM) [12] have been widely used to represent the medical image characteristics that are inaccessible to human observers. Recently, local binary patterns (LBP) have been widely used for medical image analysis. The combination of LBP and gray level generates a powerful texture descriptor in classifying three types of Emphysema and lung regions [13, 14].

Classifying diseases in lung CT images is not a simple task. The diseases are similar and only can be classified by professional radiologist. However a lot of CAD systems have been developed to assist radiologist in identifying abnormal regions.

Kim et al. [17] and Park et al. [16] proposed an implementation of shape feature in the detection of obstructive lung diseases and the results shows improvement in classification sensitivity compared to feature based on texture only. However, their proposed system is dependent on the region size, e.g., 16x16, 32x32 and 64x64 pixels. Gathering region images from CT image is not an easy task especially with fixed size of region. Their system shows a good performance in diagnosing large number of disease classes compared to those of other systems [4, 13] which diagnose only specific diseases. In order to discriminate large number of diseases, most of the CAD systems combine large number of features [16, 17, 5]. The disadvantage of this kind of system is low efficiency. This is because the system needs to execute a lot of feature extraction algorithms to diagnosis the disease.

To increase the efficiency while preserving the high sensitivity, a new feature is desired. In this paper, a novel feature is called the continuous local histogram (CLH) is introduced. CLH integrates three basic types of features which are texture feature, shape feature and brightness to increase the discrimination power. Compared to the Kim et al. system, CLH only use one powerful feature from each type of feature explained before while Kim et al. utilized 13 texture features and 11 shape features in their system. CLH is a dense descriptor since it is constructed by analyzing the smallest region in an image which is a 3x3 pixels region. Because of that, CLH can be generated from the all size of images and does not possess the region size dependency setback. The proposed system has been tested in classifying hardly classified bronchiolitis obliterans (BO) lung diseases and normal lung region which results in nearly perfect classification sensitivity.

The remainder of this paper is organized as follows: in Section 2, related works are presented; in Section 3, detailed explanation of CLH feature descriptor is presented; experimental evaluations are described in Section 4 and finally conclusions and future works are given in Section 5.

II. RELATED WORKS

A. Bronchiolitis Obliterans Lung Diseases

Bronchiolitis obliterans (BO), also called obliterative bronchiolitis (OB) and constrictive bronchiolitis (CB), is a rare and life-threatening form of non-reversible obstructive lung disease in which the bronchioles (small airway branches) are compressed and narrowed by fibrosis (scar tissue) and/or inflammation. BO is also sometimes used to refer to a particularly severe form of pediatric bronchiolitis caused by adenovirus. It is a lung disease characterized by fixed airway obstruction. Inflammation and scarring may occur in the airways of the lung, resulting in severe shortness of breath and dry cough. Figure 1 shows an example of the low attenuation lung disease which is the BO. The circled are in the image correspond to the BO region. As it can be seen, the region in the circle is a little darker than the other region in the lung but may seem similar to the other regions of the lung. This shows that the classification between BO and normal lung region is not a task. Only the eye of an experience radiologist can differentiate between a BO region and a normal region.

Characterizing medical images including local texture and shape analysis of lung parenchyma is potentially useful for understanding various lung diseases, as abnormalities in texture and shape can be related to disease pathology. High-resolution computerized tomography (HRCT) can afford accurate images for the detection of various obstructive lung diseases, such as Bronchiolitis Obliterans.

Figure 1. Bronchiolitis Obliterans

Features on the thin-section HRCT images, however, can be subtle, particularly in the early stages of disease, and diagnosis is subject to inter-observer variation. The main characteristics of the images used for the detection of obstructive lung diseases are the presence of areas of abnormally low attenuation in the lung parenchyma, which, in the case of BO, the abnormal region can be detected automatically by means of attenuation thresholding. Areas of decreased parenchymal attenuation, however, are a feature of other obstructive lung diseases [16].

B. Automatic Diagnosis System

Liang et al. [5] and Peng et al. [9] have developed texture descriptors for classifying abnormal regions of lung CT images as shown in Figure 2. To locate the lung region from the CT image of lung, the contrast of the input image is enhanced using gamma correction. Then the binary image is obtained using the Otsu method [15]. Using morphology and region growing method, the noise in the image and lung vessels themselves are excluded to obtain the lung region without the vessels. For the feature extraction, the texture feature of the sub-region separated from the lung image is extracted using texture descriptors. This operation consumes a lot of time because there are a lot of sub-region need to be classified.

K. Muzzammil et al. [25] proposed a method to speed up the classification process by using pre-detected of abnormal region. Some of the sub-region may not contain any Emphysema and the classification of these sub-regions is useless. To decrease the time consumption of Emphysema region, some sub-regions that have zero percentage of having Emphysema is removed by analyzing the size of the low attenuating region. Lastly the resulting features are used to determine whether it contains abnormal region or not in the region classification step.

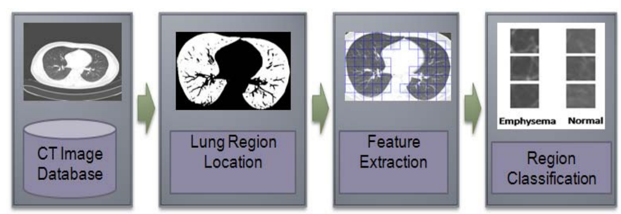

Figure 2. The Feature Extraction System

III. THE PROPOSED METHOD

A chest CT image can appear in different conditions depending on its type and dose. A HRCT image has more details and contains more texture information of the lung. A standard CT image of the lung contains more homogeneous region than the textured region, and the image is blurrier than the HRCT image. Generally, a high radiation dose results in high-resolution images, while a lower dose leads to increased image noise and results in unsharp images [18]. Because of that, the proposed CLH method is specially build for HRCT images instead of normal CT images.

A. The Local Feature

Three type of local feature are selected to be combined continuously into a feature vector. The local features are the local brightness feature, local texture feature and local shape feature. These features are selected because they contain the most beneficial information of the smallest region available in an image which is a 3x3 region.

1) The brightness feature

Image can be saved in various formats according to the application. For medical purpose, HRCT image are originally saved in the Digital Imaging and Communications in Medicine (DICOM) format [19]. The DICOM format is usually has one channel with bit-depth around 12bit to 16 bit. In order to get more information from the HRCT image, DICOM format is implemented in this paper.

To attain better understanding regarding the information from the HRCT image, the grey value is not used in the analysis. Instead, the gray value is converted into Hounsfield unit (HU) [20]. The HU scale is a linear transformation of the original linear attenuation coefficient measurement.

A DICOM image can be converted to the HU using the following formula:

$$HU = grey\ value * S + I \qquad (1)$$

where S and I are slope and intercept of the HRCT image.

2) The texture feature

For texture feature, CND feature [25] is utilized in the proposed CLH. The reason is because CND is extracted locally and has high discrimination power. Moreover, the simple calculation utilized by CND is an advantage to CLH.

3) The shape feature

Common shape feature can only be extracted from large image. In order to extract shape feature from a small image, e.g. 3x3, a new shape descriptor is proposed. The new shape descriptor is called local shape (LS). And lastly, for the brightness information, CLH utilize the HU of the image. Compared to grey values, HU contain more descriptive information.

The first step is to threshold the whole image with -900 HU. This is because the low attenuating diseases often occur on the scale lower than -900 HU. After obtaining the binary window, we can refer the shape number of the binary window from the local shape list as shown in the Figure 3. As we can see from the figure, the 512 possible shapes in a 3x3 window are grouped into 70 groups. Each group contains the rotated and the inverse pattern of a certain shape. The center pixel of the 3x3 window is then replaced by the shape number from the list according to the assigned local shape.

Then the same process is done the next 3x3 window in the image. After analyzing the whole 3x3 windows in the image, we will obtain a feature image where each pixel of the feature image consists of the local shape number is obtained. The histogram of these local shape numbers is then constructed. The resulting 70 bins histogram is then used to describe the image.

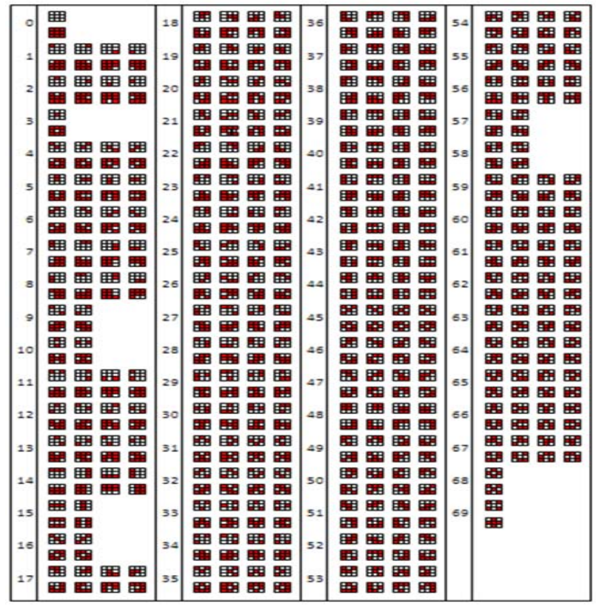

Figure 3. The local shape list, left column, the local shape number, right column, assigned local shape

B. Continuous Local Histogram

The overall CLH algorithm is shown in Figure 4 (at the end of the paper). First of all the images is converted into HU scale. Then CND, LS and HU are calculated from each window of the image. After executing the same process for each window, three feature images are obtained. Then the histograms of these three feature images are calculated. Because most of sub-regions in the lung are small, large dimension histogram is unable to generate informative histogram. Therefore, low dimension histograms need to be applied. Originally, CND will produce 256 bins histogram. But for CLH, 64 bins CND histogram is used instead. For HU, the values are clipped into the range from -1024 to -401. Then, 78 bins histogram is generated from the HU feature image. This is because low attenuating lung diseases can only occur within that range [17]. And lastly, 70 bins histogram is generated from the LS. The histograms are then combined into one long histogram.

However this feature dimension is too high and implementing high dimensional feature vector will result in low efficiency in detecting and categorizing the abnormal region in HRCT images. In order to reduce the feature dimension, principle component analysis (PCA) is implemented. Ten significant principle components are selected as the final feature vector of the region. Ten principle components are chosen because based on a classification experiment, ten is a sufficient number of vectors. It can discriminate the diseases distinctly while maintaining high classification speed. This ten dimensional feature vector are then used to represent each disease in the automated system.

IV. EXPERIMENTAL STUDIES

A. Experiment Setup

For the classification experiment, DICOM image is utilized in order to extract more information from the HRCT images. The images were selected from HRCT (Sensation 16, Siemens, Erlangen, Germany) obtained in 9 healthy subjects (NL, n=100), 10 patients with Bronchiolitis Obliterans (BO, n=100). Ethical approval was obtained from the local institutional review board and written informed consent was waived. Images were acquired with 1.23mm of collimation and 10mm of interval with scan parameters of 120kV and 50mAs. The scan coverage is 1cm above lung apex until diaphragm.

The performance of CLH is compared with two other methods which are commonly used in medical image analysis which are the LBP [13] and GLRLM [12]. The experiment is conducted on computer with an Intel Core2Duo 2.33 GHz quad core processor and 2GB of main memory. All of the codes are written in MATLAB environment with Window XP operating system.

As for the classifier, AdaBoost machine learning algorithm is implemented [21]. AdaBoost is a meta-algorithm, and can be used in conjunction with many other learning algorithms to improve their performance. It is adaptive in the sense that subsequent classifiers built are tweaked in favor of those instances misclassified by previous classifiers. Three weak classifiers are used with the AdaBoost algorithm. There are the nearest neighbor (NN), linear discriminant analysis (LDA), and Naïve Bayes (NB) classifiers [22, 23, 24]. After performing an simple classification experiment, the result shows that the NN weak classifier is the best of classifying the BO compared to other weak classifiers. So the Adaboost NN (A-NN) is used in the experiment for comparing the performance of BO lung disease classification. The NN classifier uses the Euclidean distance as the similarity measure. The AdaBoost algorithm is iterated 15 times in order to see the effect of the iteration number.

Three evaluations of the classification are recorded which are accuracy, sensitivity and specificity. The sensitivity and specificity are calculated using the following formula:

$$Sensitiviy(\%) = \frac{True\ positive}{True\ positive + False\ negative} \times 100 \quad (2)$$

$$Specificity(\%) = \frac{True\ negative}{False\ positive + True\ negative} \times 100 \quad (3)$$

where true positive, true negative, false positive and false negative are as follows:

- True positive: the number of abnormal regions that is correctly classified.
- True negative: the number of normal regions that is correctly classified.
- False positive: the number of normal regions that is incorrectly classified as emphysema regions.
- False negative: the number of abnormal regions that is incorrectly classified as normal regions.

The receiver operating characteristic (ROC) curve is also calculated to compare the performances of each method. To evaluate the ROC curve, the area under curve (AUC) is calculated so that the performance of each method can be compared numerically.

B. Evaluation of the Classification Performance

In order to see the effects of the iteration number for the AdaBoost algorithm, the classification accuracy of CLH is recorded in several different iterations. The classification is executed 100 times in order to execute the ANOVA test. The accuracy result is shown in Table 1.

TABLE I. THE CLASSIFICATION ACCURACY OF CLH

Method	N	BO	NOR	Overall
A-NN	1	72.90	99.05	85.98
	5	91.97	99.99	95.98
	10	95.18	100	97.59
	15	96.03	100	98.02

As we can see, the iteration number does affect the accuracy result. From the ANOVA test, it can be concluded that number of iteration significantly affects the classification accuracy for A-NN classifier ($F=28.69$, $p<0.01$). However, the iteration has a limit. After certain number of iteration, the accuracy will maintain or sometime will decrease. From the experiment, it is observed that 15 is the optimum iteration number to achieve the best classification accuracy.

TABLE II. THE AVERAGE CLASSIFICATION TIME OF CLH, LBP, AND GLRLM

Sensitivity				
Method	Feature	BO	NOR	Overall
A-NN	CLH	96.30	100	**98.15**
	LBP	88.00	58	**73.00**
	GLRLM	73.60	78	**75.8**
Specificity				
Method	Feature	BO	NOR	Overall
A-NN	CLH	98.66	97.92	**98.29**
	LBP	68.10	74.10	**71.10**
	GLRLM	74.92	74.14	**74.53**

The sensitivity and specificity performances of CLH are compared with those of LBP and GLRLM using the A-NN classifier. The classification is executed a hundred times with AdaBoost iteration of 15 and the average results are recorded. The results are shown in Table 2. As it can be seen, the proposed CLH achieves the best average sensitivity and specificity with over 98.15% which are 20% higher than those of LBP and GLRLM. This shows how powerful the CLH in extracting feature from five classes of diseases and one class of normal region.

The efficiency test is also conducted to compare the classification time of the three methods namely, the CLH, LBP and GLRLM. As we know, the final feature vector of CLH is 10 dimensions while LBP is 256 dimensions and GLRLM is 7 dimensions. The average classification time of all six classes using AdaBoost iteration of 15 is recorded for each method. The result is shown in Table 3. From the result it can be concluded that the lower the feature vector dimension, the lower the classification time is. Because the dimension of CLH feature vector is small, it achieves low computation time (F=30.51, p<0.01). Although GLRLM obtains the lowers classification time, it classification time difference between CLH is small and the classification performance are every low compared to CLH.

TABLE III. THE AVERAGE CLASSIFICATION TIME OF CLH, LBP, AND GLRLM

CLH		LBP		GLRLM	
Classifier	Time(s)	Classifier	Time(s)	Classifier	Time(s)
A-NN	9.3	A-NN	318.1	A-NN	7.3

For a summary statistic of the performance, the ROC curve is computed using the feature vectors of the histograms from each method. The ROC curves of the pair BO and normal region for CLH, LBP and GLRLM are shown in Figure 5. From the curves, it can be seen that the performance of CLH is better than those of LBP and GLRLM. CLH manages to obtain high true positive rate even with low false positive rate.

In order to observe the results numerically, the AUC is calculated. The nearer the AUC to 1 is the better the performance is. Table 4 shows the AUC of the BO-NOR method. It achieves 0.9 AUC using CLH while those of LBP and GLRLM are 0.7775 and 0.8575, respectively. From the result, it can be seen that the performance of CLH is more than 20% than those of LBP and GLRLM.

TABLE IV. AUC OF BO-NOR FOR CLH, LBP, GLRLM

CLH	LBP	GLRLM
0.9	0.7775	0.8575

V. CONCLUSIONS AND FUTURE WORKS

This paper introduced a new automated system for diagnosing low attenuating lung called the Bronchiolitis Obliterans. A simple but effective region feature named CLH is proposed to extract important feature that can describe the diseases for the automated diagnosis. From the results, it can be seen that the proposed CLH produced high sensitivity compared to those of LBP and GLRLM. It also consumed low computation time due to its small feature dimension. Clearly, the proposed automated system is vigorous and should be employed in the real world industries.

As for the automated system, the next step is to compare its performance with the professional radiologist in segmentation of the lung according to the diseases. The pre-detection system will also be applied in the segmentation in order to see the accuracy and the efficiency of the segmentation.

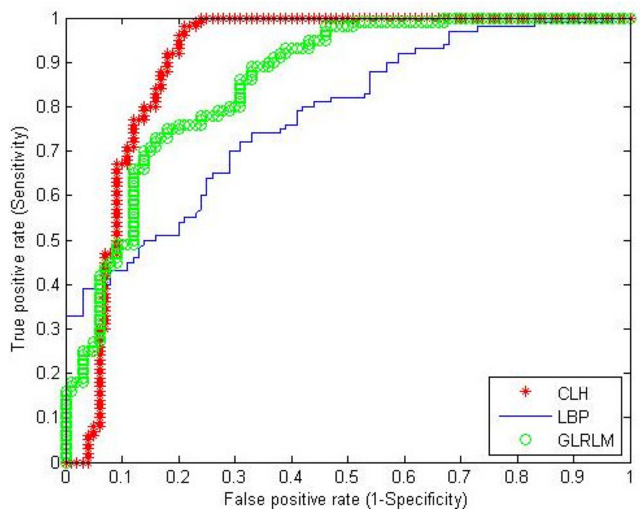

Figure 5. The ROC curves of BO-NOR pair

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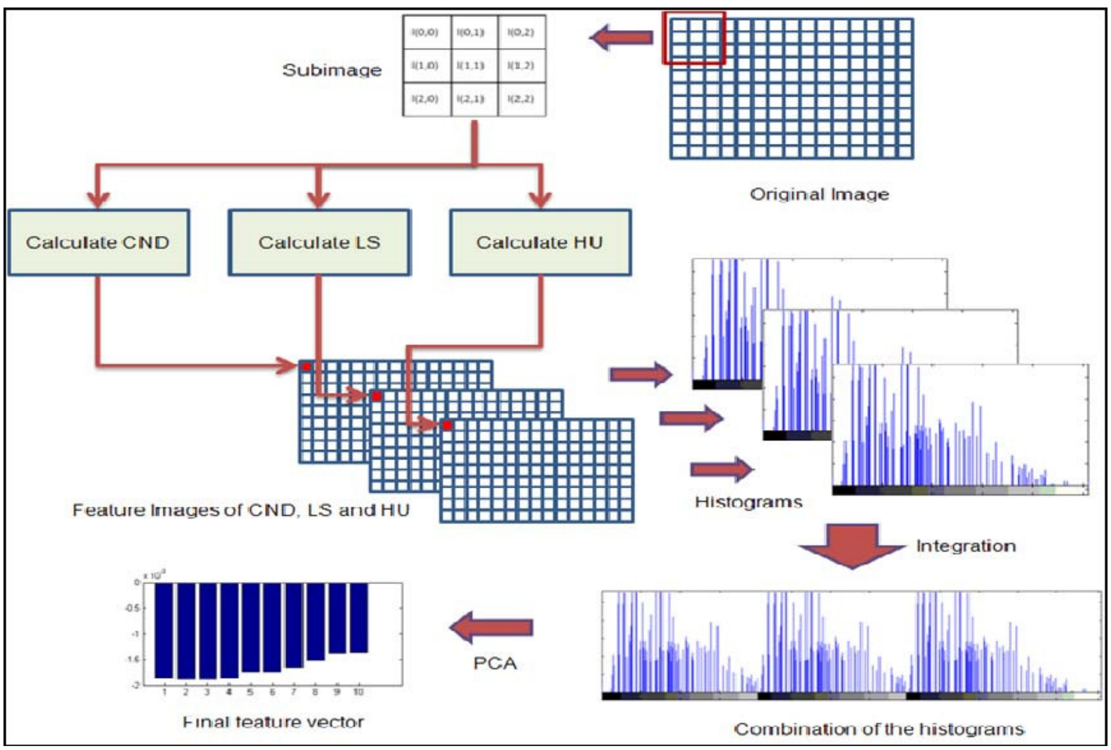

Figure 4. The Algorithm of CLH.