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Feature Based Classifiation Of Lung Tissues For Lung Disease Diagnosis

V.Lakshmi[1], Ms. P.Krisnaveni[2], Mrs. S.Ellammal[3]

PG scholar, Sri Vidya College of Engineering and Technology[1]

Assistant Professor, Sri Vidya College of Engineering and Technology[2]

Associate Professor, Sri Vidya College of Engineering and Technology[3]

ABSTRACT: In this paper, a new method for Lung tissue Classification using Patch adaptive sparse approximation with two feature descriptors is proposed. Operator assisted classification methods are impractical for large amounts of data .High resolution Computed Tomography images contain a noise caused by operator performance which can lead to serious inaccuracies in classification. We design two new feature descriptors for higher feature descriptiveness, namely the rotation-invariant Gabor-local binary patterns (RGLBP) texture descriptor and multi-coordinate histogram of oriented gradients (MCHOG) gradient descriptor. Each image patch is then labeled based on its feature approximation from reference image patches. Decision making was performed in two steps i) Feature extraction using the two feature descriptors ii) classification using Patch adaptive sparse approximation.

KEYWORDS: Adaptive, gradient, reference, texture.

I. INTRODUCTION

The interstitial lung disease (ILD) represents a group of more than 150 disorders of the lung parenchyma[1]. Most of these cause progressive scarring of lung tissues and eventually affect breathing. Determining the specific type of disorder is important for treatment, and in conjunction with other methods, such as blood tests and pulmonary function tests, imaging scans are often accurate diagnosis. In particular, HRCT imaging is quickly becoming the standard practice with its high imaging quality. Different ILDs normally exhibit different combinations of tissue patterns on HRCT images , and differentiating the tissue patterns is critical to identify the actual type of ILD. However, interpreting the HRCT images for lung diseases is challenging even for trained radiologists . Patients also have different physical conditions and medical histories, hence even those with the same type of ILD could display quite different tissue patterns. As a consequence, manual interpretation of the images

Fig 1Tissue patterns

From left to right: normal, emphysema, ground glass, fibrosis, and micronodules could be error prone, especially when the radiologists under heavy workload with short time frames. It is thus suggested that an automatic system for differentiating the tissue patterns would be useful to provide initial screening or second opinions. In this study, we focus on classification of five categories of lung tissues on HRCT images—normal, emphysema, groundglass, fibrosis, and micronodules, which are highly prevalent among the main type of ILDs.

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II. RELATED WORK

Image classification is normally performed in two stages: feature extraction for encoding the image features as feature descriptors, and labeling of image categories using supervised approaches. Being an active research field for a long time, most of the image classification techniques have been applied to a wide range of imaging problems, including the lung CT images. We will thus review mainly the recent works on lung CT images to cover the popular methodologies, and only include studies from other imaging domains if the proposed methods are not normally used for lung studies [1].Zhengyi Yang, Jeiran Choupan explained that tissue Classification for PET/MRI Attenuation Correction using Conditional Random Field and Image Fusion to inclusion of PET data improved the classifier's performance in terms of classification accuracy. But feature set used in classifiers plays a critical role and finding the relevant features to the learning task is often too expensive to explicitly enumerate and compare all the candidate feature subsets[2].S.Sivakumar, C.Chandrasekar explained that Detection of lung nodules is a challenging task since the nodules are commonly attached to the blood vessels. This paper aims to develop an efficient lung nodule detection scheme by performing nodule segmentation through fuzzy based clustering models; classification by using a machine learning technique called Support Vector Machine (SVM). This methodology uses three different types of kernels among these RBF kernel gives better class performance. Advantage of this method is better classification. Demerit is even though FCM algorithm yields good results for segmenting noise free images, it fails to segment images corrupted by noise[3]. Anam Tariq, M. Usman Akram proposed that a computerized system for lung nodule detection in CT scan images. The automated system consist of two stages1.feature extraction 2.classifiation.The segmentation process will result in separating lung tissue from rest of the image and only the lung tissues under examination are considered as candidate regions for detecting malignant nodules in lung portion. Advantage of this method is accuracy. Demerit of this method is low feature extraction[4].Adrien Depeursinge, Dimitri Van de Ville proposed that near-affine-invariant texture descriptors derived from isotropic wavelet frames for the characterization of lung tissue patterns in high-resolution computed tomography HRCT imaging to provide classification accuracy of 76.9%.But 3-D WTs are not appropriate for analyzing HRCT image series because filtering along the z-axis with a very low axial resolution (20 to 50 slices with 10-mm distance) leads to coarse blurring of the relevant information[5].Ulas bagsi ,Jianhua yao presents a novel computer-assisted detection (CAD) system for automatically detecting and precisely quantifying abnormal nodular branching opacities in chest computed tomography (CT), termed tree in bud(TIB) opacities by radiology literature to accurate lung tissue classification but it takes more time for computational[6].V.Kumar, S.Jeyanthi gives information about automated vessel tree segmentation Algorithm. This method utilizes Fuzzy Support Vector Machine (SVM) classifier which improves traditional SVM by adding fuzzy membership to training sample to indicate degree of membership of this sample to different class. Consequently it reduces noises and outliers in data and enhances performance and accuracy of SVM but feature extraction is low [7]. Qi song, Milan Sonka presents an automatic algorithm for pathological lung CT image segmentation that uses a graph search driven by a cost function combining the intensity, gradient, boundary smoothness, and the rib information. They use KNN classifier for feature extraction. This method has better performance because image intensity, and image gradient are combined into the cost function for graph search algorithm .But this method have high computational time [8]. Jianhua Yao, Andrew Dwyer suggested that to develop and test a computer-assisted detection method for identification and measurement of pulmonary abnormalities on chest CT in cases of infection. This method developed could be a potentially useful tool for classifying and quantifying pulmonary infectious disease on CT. Forty Chest CTs were studied using texture analysis and support vector machine (SVM) classification to differentiate normal from abnormal lung regions on CT. This method has high texture feature extraction but accuracy is low [9].Panayiotis, Korfiatis gives brief information about an automated scheme for Texture-based identification and characterization of interstitial pheumonia patterns in lung multidetector CT. This method has high Feature extraction because it uses 3-d gray level cooccurrence features, stepwise discriminant analysis (SDA),K-NN classifier. But this method has high computational time [10].

III. PROPOSED WORK

In this work, we propose a new image classification method for lung tissue .

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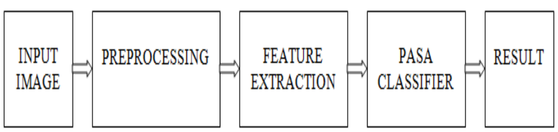
In this work, we propose a new image classification method for lung tissue patterns, based on feature-based image patch approximation.

A set of texture and gradient features are extracted for each image patch, and two new feature descriptors are proposed: 1) a new rotation-invariant Gabor-LBP(RGLBP) feature descriptor to represent rich texture features integrating multi-scale Gabor filters and LBP histograms; 2) a new multi-coordinate HOG (MCHOG) descriptor to extract the gradient features while accommodating rotation variance with radial-specific coordinate systems.

Each image patch is then classified using new patch-adaptive sparse approximation (PASA) algorithm, designed for better classification accuracy in the sparse representation.

BLOCK DIAGRAM



3.1 Input image

Input image is taken as gray level image. Because it has few level(0-255) compared to RGB image.

3.2 Preprocessing

Preprocessing step is used to remove the noise..They are,

- Erosion
- Median filter
- Dilation
- Edge detection

A. Erosion:

Two very common morphology operators are Dilation and Erosion. A set of operations that process images based on shapes. Morphological operations apply to an input image and generate an output image.

At each translated location, the structuring element values are subtracted from the image pixel values and the minimum is computed. To compute the erosion of a binary input image by this structuring element, consider each of the foreground pixels in the input image. For each foreground pixel (input pixel) superimpose the structuring element on top of the input image so that the origin of the structuring element coincides with the input pixel coordinates. If for every pixel in the structuring element, the corresponding pixel in the image underneath is a foreground pixel, then the input pixel is left as it is.

B. Median filter

In signal processing, it is often desirable to be able to perform some kind of noise reduction on an image or signal. The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise. Median filtering is one kind of smoothing technique, as is linear Gaussian filtering. All smoothing techniques are effective at removing noise in smooth patches or smooth regions of a signal, but adversely affect edges. Often though, at the same time as reducing the noise in a signal, it is important to preserve the edges.

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C. Dilation

Dilation is the dual of erosion. At each translated location, the structuring element values are subtracted from the image pixel values and the minimum is computed. The basic effect of the operator on a binary image is to gradually enlarge the boundaries of regions of foreground pixels (i.e. white pixels, typically). Thus areas of foreground pixels grow in size while holes within those regions become smaller. The dilation operator takes two pieces of data as inputs. The first is the image which is to be dilated. The second is a usually small set of coordinate points known as a structuring element also known as a kernel. It is this structuring element that determines the precise effect of the dilation of the input image.

D. Edge detection

The Sobel operator is used in image processing, particularly within edge detection algorithms. Technically, it is a discrete differentiation operator, computing an approximation of the gradient of the image intensity function. At each point in the image, the result of the Sobel operator is either the corresponding gradient vector or the norm of this vector. The Sobel operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical direction and is therefore relatively inexpensive in terms of computations.

3.3 Feature extraction

In feature extraction first full lung images are taken. RGLBP and MCHOG is applied to full lung images for texture feature and gradient feature extraction. Then this image is cropped and given as name using PASA. Based on our visual analysis of lung images, it is observed that texture, intensity and gradient distribution of soft tissues within an image patch are quite informative and discriminative for different categories of lung tissues. Therefore, a patch-wise feature set, combining texture and gradient features are extracted for each image patch. And motivated by the recent works in the general imaging domain, we design a set of features based on the popular LBP and HOG descriptors, with modifications introduced for better feature descriptiveness.

A. Texture Description

The LBP feature describes the spatial structure of local image texture, and can be easily configured to be multi-resolution and rotation-invariant. However, the LBP feature might capture too many image details, and introduce large degree of unnecessary feature variations within the same tissue category. On the other hand, the multi-scale and multi-orientation representation of Gabor filters is often demonstrated as a highly effective texture descriptor. However, being rotation-variant, the Gabor filters become not directly suitable for our problem; but the multi-scale nature is quite useful for computing multi-resolution LBP features. Therefore, to incorporate rich texture information while attempting to minimize intra-category variations, we choose to design a new rotation-invariant Gabor-LBP(RGLBP) texture descriptor to incorporate the multi-scale property of Gabor filters and the rotation-invariant property of LBP features.

B. Gradient Description

Gradient distribution of an image is a different type of feature in complementary to the texture and intensity features. It is potentially very useful for discriminating pathological and normal lung tissues, since the former type often contains small segments that are less common in the normal lung. Among the various types of gradient-based features, the HOG feature has been suggested as very effective, especially when coupled with LBP features .

A problem with HOG features for lung images is, however, that it represents the distribution of absolute gradient orientations and hence is not invariant to rotations. While normally the rotation issue is tackled by assigning a dominant orientation based on local image statistics, such as SIFT .It is rather not intuitive to perceive a dominant orientation for image patches with complex textures. Therefore, inspired by the work on a SIFT-related rotation-invariant descriptor ,we design a new multi-coordinate HOG (MCHOG) descriptor to accommodate the possible rotations.

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3.4 Approximative patch classification

The next step is to classify each image patch into one of the five tissue categories. Considering that lung images normally exhibit quite different patterns even within the same tissue category, we expect that even with the comprehensive feature design, large intra class variations would still exist. Therefore, we would like to use a classification scheme that is especially effective in handling such issues. And we thus design a data-adaptive and non- parametric approach, namely the patch-adaptive sparse approximation(PASA) method, to classify an image patch based on the closeness of approximation by other image patches from each tissue category.

IV. IMPLEMENTATION

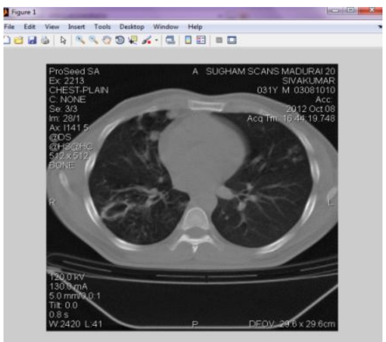

Fig 2 Input image

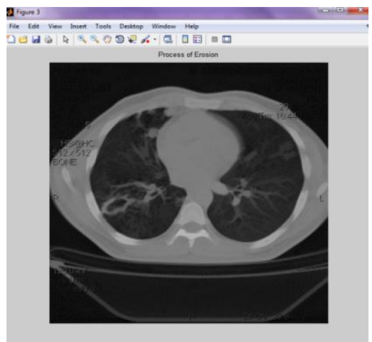

Fig 3 Erosion image

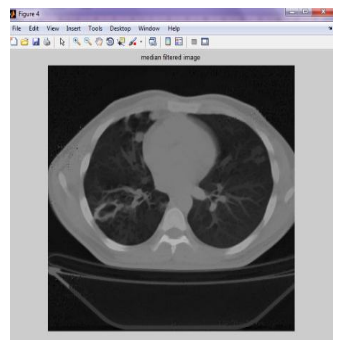

Fig 4 Median filter image

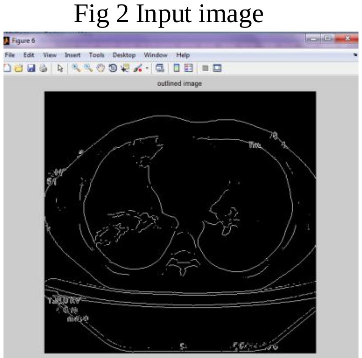

Fig 6 Edge detection using SOBEL

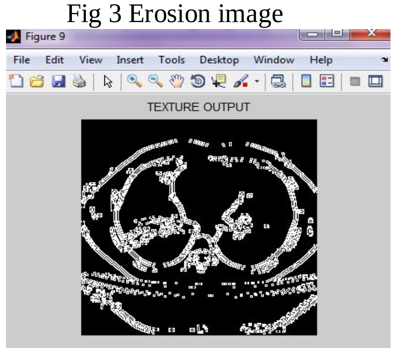

Fig 7 Texture descriptor output

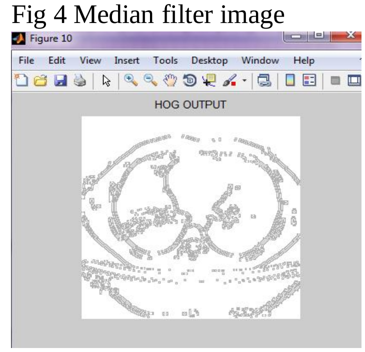

Fig 8 Gradient descriptor output

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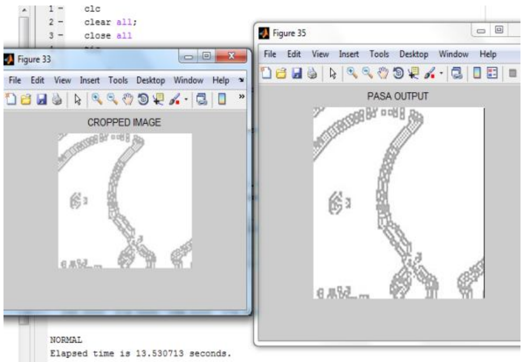

Fig 9 Normal lung tissue

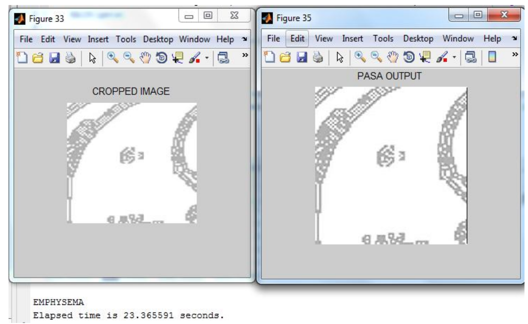

Fig 10 Emphysema lung tissue

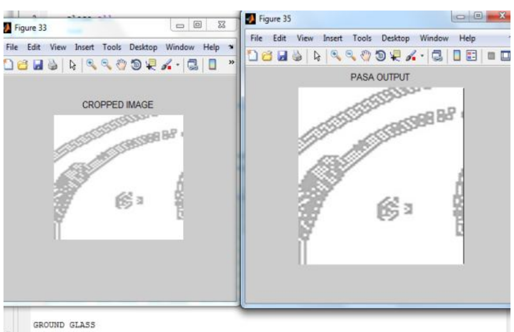

Fig 11 Ground glass lung tisue

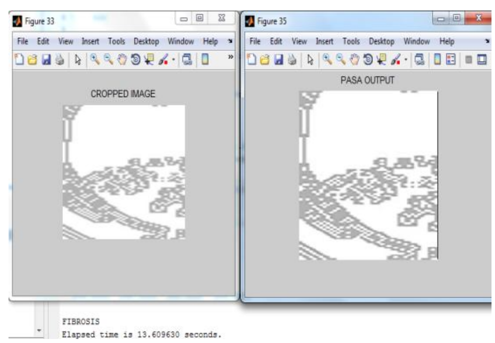

Fig 12 Fibrosis lung tissue

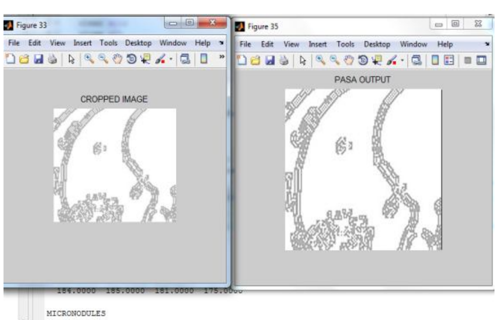

Fig 13 Micronodules lung tissue

V. CONCLUSION AND FUTURE WORK

An automatic classification method for lung HRCT images is presented in this paper. Five categories of lung tissues – normal, emphysema, ground glass, fibrosis and micronodules—that are important for ILD disease diagnosis, are the main objects to be differentiated. To tackle the challenges in low inter-class distinctions and high intra-class variations, we have designed a feature-based image patch approximation method. First, an image patch is represented as a feature vector, based on our proposed RGLBP texture and MCHOG gradient descriptors. Then, the image patch is classified into one of the five tissue categories, using our proposed PASA classifier based on reference image patches.In future fast PASA is used for fast classification.

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