

ENHANCED IMAGE PATCH APPROXIMATION FOR LUNG TISSUE CLASSIFICATION USING FEATURE EXTRACTION

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Abstract— *The growing size and number of the medical images necessitated the use of computers to facilitate processing and analysis. In medical world diagnostic Imaging is an invaluable and important tool for early detection of diseases. An enhanced feature descriptor that categories lung tissues in High Resolution Computed Tomography (HRCT) images used for Computer Aided Diagnosis is proposed in this paper. The images are divided into multiple Image Patches called AROI (Annotated Region of Interest). Image features like Texture, intensity and gradient are considered for feature extraction and classification. Labeling is done using a new patch-adaptive sparse approximation method. The proposed method is evaluated on a publicly available Interstitial Lung Disease (ILD) database to show the performance improvement.*

Keywords— *Gradient, Texture, feature descriptor, classifiers.*

I. INTRODUCTION

Interstitial lung disease (ILD), also known as diffuse parenchyma lung disease (DPLD), refers to a group of lung diseases affecting the interstitium (the tissue and space around the air sacs of the lungs). It concerns alveolar epithelium, pulmonary capillary endothelium, basement membrane, perivascular and perilymphatic tissues.

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 used for 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.

Differentiating the tissue patterns is critical to identify the actual type of ILD. Patients having different physical conditions and medical histories even those with the same type of ILD could display different tissue patterns.

Manual Interpretation of the images could be error prone, when the radiologists are under heavy workload with short time frames[1]. It is thus suggested that an automatic system

for differentiating the tissue patterns would be useful to provide initial screening or second opinions.

II. RELATED WORK

We focus on classification categories of lung tissues on HRCT images—normal, emphysema, ground glass, fibrosis, and micro nodules, which are highly prevalent among the main types of ILDs. Examples of these tissue patterns are shown in Fig. 1.

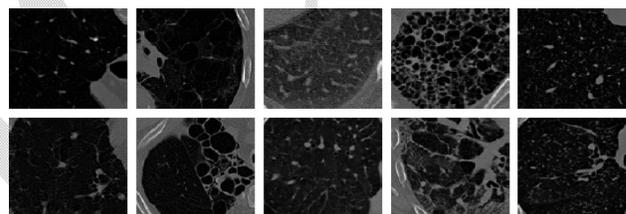


Fig 1 : Five categories of Lung Tissues –normal, emphysema, ground glass, fibrosis, and micro nodules

It can be seen that while in general there are perceivable differences between the different categories, the visual distinctions between different categories are sometimes subtle, and the pattern variations within the same tissue category are rather obvious. 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.

Visual features of lung tissues can be described numerically in a number of ways[3]. The simple gray-level distributions are often used since the intensities well represent the physical properties of lung tissues[4]. Second-order statistics such as the Gray-Level co-occurrence matrices (GLCM) and Run Length Encoding (RLE) [5] have also been widely incorporated for additional feature information.

Another type of popular feature extraction technique is based on filters, e.g., Gaussian and wavelets [6],[8] to highlight specific image features such as edges. Other features such as shape and spatial contexts are also used for certain applications in lung imaging. The above feature extraction techniques are usually defined for image patches, or often referred to as regions-of-interest (ROI) with fixed sizes. In some cases, however, the objective is to classify a larger annotated ROI area containing multiple image patches (denoted as AROI for clarity). With patch-based processing, it is easier to compute features, and such features would exhibit lower intra-class variations than the AROI-level features. An AROI normally displays repetitive patterns with spatial correlation between patches not as informative as the local features; and hence it is quite reasonable to perform patch-level processing. An example image illustrating AROI and patch is shown in Fig. 2.

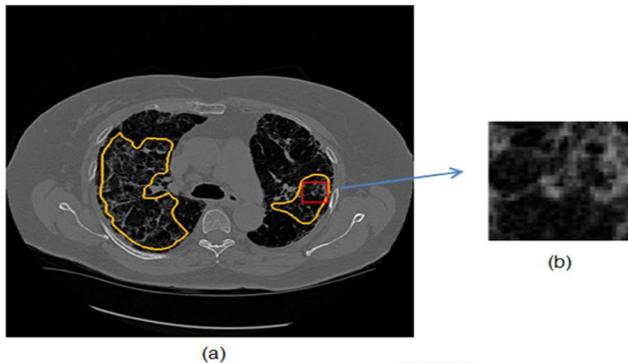


Fig 2: Sample lung HRCT image slice shown in (a), in which the orange contours indicate two AROIs, and the red box highlights an image patch that is shown in (b).

The next stage is to perform labeling of these descriptors for image classification. The labeling is usually based on supervised approaches, and the most commonly used classifiers include k-nearest neighbor (k-NN), Support vector machine (SVM), Linear discriminate analysis (LDA), Bayesian classifiers, and Artificial neural network (ANN). Among these, the SVM classifier is normally highly effective, but would be error prone if the feature spaces exhibit considerable overlaps, especially with images of different categories appearing quite similar. The k-NN classifier is intrinsically capable of accommodating the intra-class variations, but the feature descriptors are usually not descriptive and discriminative enough to achieve accurate classification based on simple distance measures. A different type of classification—the sparse representation Method can be used in which the basic idea is that, a query image is classified based on minimum reconstruction error from a set of reference images.

Such a method can be considered analogous to k-NN but the distance measure is with the optimal combination of multiple references that are selected adaptively to the query image. It is

also quite effective in handling intra-class variations, with classification based on reference samples rather than learned parametric models. The sparse representation is originally aimed to optimize reconstruction, it does not necessarily lead to accurate classification; and for cases with low inter-class distinctions, an additional classifier (e.g., SVM) seems still necessary.

III. PROPOSED WORK

In this paper a new image classification method for lung tissue patterns, based on feature-based image patch approximation is proposed. Our main methodological contributions are threefold. First, a set of texture, intensity, and gradient (T-I-G) features are extracted for each image patch, and two new feature descriptors are proposed:

- 1) A new rotation-invariant Gabor-Local Binary Pattern (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.

Second, each image patch is then classified based on reference dictionaries with a new patch-adaptive sparse approximation (PASA) algorithm, designed for better classification accuracy in the sparse representation:

- The image patch labeling is enhanced with a statistical measure of the sparse coefficients to measure the minimum discrepancy.
- A patch-specific adaptation method is designed based on pair wise feature distances to alter the feature values of the reference dictionaries for more discriminative approximation;
- A feature-space weighting scheme is designed based on overlapping of feature distributions for feature distance computation.

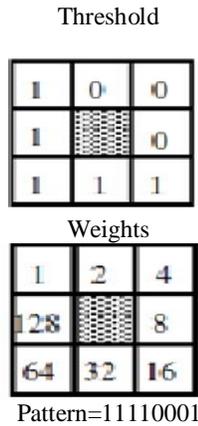
Third, the labeling of the annotated Region of Interest (AROI) is finally obtained based on probabilistic estimation from the patch-wise classification. And the proposed method is evaluated on the publicly available ILD database, showing promising performance improvements over the state-of-the-art results reported for the same database.

Furthermore, since our proposed feature descriptors (RGLBP and MCHOG) and the approximate image classification algorithm (PASA) are designed based on few assumptions about the problem domain, these methods are thus extensible to other medical imaging problems as well.

IV. METHODOLOGY

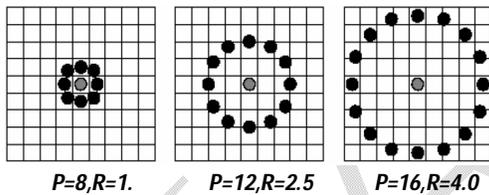
4.1 Existing LBP Methodology

A binary code that describes the local texture pattern is built by thresholding a neighborhood by the gray value of its center.



4.2 Proposed LBP Methodology

The original definition is extended to arbitrary circular neighborhoods



Main methodology contributions are three-fold.

4.2.1 Pre Processing:

Preprocessing of data is done for the following reasons.

- Reduction of artifacts (bugs in images)
- Image noise reduction
- Leveling (harmonization) of image quality for clearing the image’s different basic condition e.g. different exposure parameters

Texture-Intensity –Gradient (TIG) extraction

An image patch is denoted as P comprising of X x Y pixels $P=\{p_i: i=1, \dots, X \times Y\}$ and I_i as the intensity value of pixel p_i . The Pixel p_i is also indicated by its coordinate as $p(x, y)$ and intensity $I(x, y)$.

A T-I-G feature vector $f(P)$ is then derived for the image patch P Feature vector $f(P)$ of $H=(Sx36+32+Kx9)$ dimensions is extracted for each image patch P.

$$f(P)=\{RGLBP(P),IH(P),MCHOG(P)\} \text{_____} (1)$$

Where S= number of scales
K=cells for feature computation

Based on our initial study on a rather small set of images, it is observed that in order not to smooth out the small tissue patterns, three spatial scales (S=3) are quite adequate . In order not to introduce too much spatial information causing extra feature variations, four square cells (K=4) need to be used.

The three parts of the feature vector – RGLBP (P), IH (P) and MCHOG (P) are normalized to have a common mean value, so they would carry similar weights in the overall feature description.

The mean of a certain feature, e.g., RGLBP (P), is computed by dividing the sum of its feature elements with its feature dimension. Then by linear rescaling of IH (P) and MCHOG (P), their means are aligned to the same mean as RGLBP (P).

Rotation-invariant Gabor Local Binary Pattern(RGLBP) descriptor

To incorporate rich texture information while attempting to minimize intra-category variations a new rotation invariant Gabor LBP(RGLBP) texture descriptor is designed to incorporate the multi-scaled property of Gabor Filters and the rotation- invariant property of LBP features.

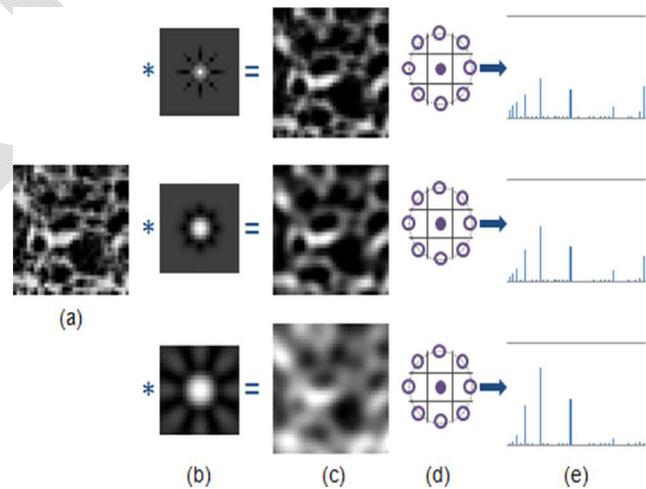


Fig. 3: Illustration of the proposed RGLBP texture descriptor.
(a) An image patch.
(b) Rotation-invariant Gabor filter bank with three scales.
(c) The Gabor filtered images.
(d) Structure of LBP with radius 1 and 8 neighboring pixels.
(e) The derived rotation-invariant histogram for each scale, with x-axis as the feature dimension and y-axis as the feature value.

Multi-coordinate Histogram Of Gradient (MCHOG) descriptor

Among the various types of gradient-based features, the HOG feature has been suggested as very effective when coupled with LBP features. A problem with HOG features

for lung images is that it represents the distribution of absolute gradient orientations and hence is not invariant to rotations.

The rotation issue is tackled by assigning a dominant orientation based on local image statistics, such as SIFT[10]. Inspired by the work on a SIFT-related rotation-invariant descriptor a new *multi-coordinate HOG (MCHOG)* descriptor to accommodate the possible rotations will be designed.

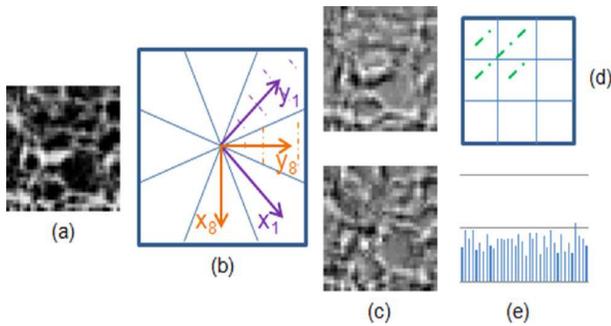


Fig. 4: Illustration of the proposed MCHOG gradient descriptor.

- (a) An image patch.
- (b) The radial-specific coordinate systems, with the light blue lines indicating the division of the radial sections, and purple and orange arrows representing the xy coordinates of radial section $P1$ and $P8$.
- (c) The gradients computed on y (upper) and x (lower) directions, based on the radial-specific coordinate systems.
- (d) Subdivision of four overlapping cells, with the green shaded area representing the first cell.
- (e) The derived gradient histogram, with x -axis as the feature dimension and y -axis as the feature value.

4.2.2. Image classification

With the patch-wise T-I-G feature vector, 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.

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 will be designed.

Denoting the five tissue categories—normal, emphysema, ground glass, fibrosis, and micro nodule—as T_N, T_E, T_G, T_F and T_M , the objective here is to assign each image patch a category label.

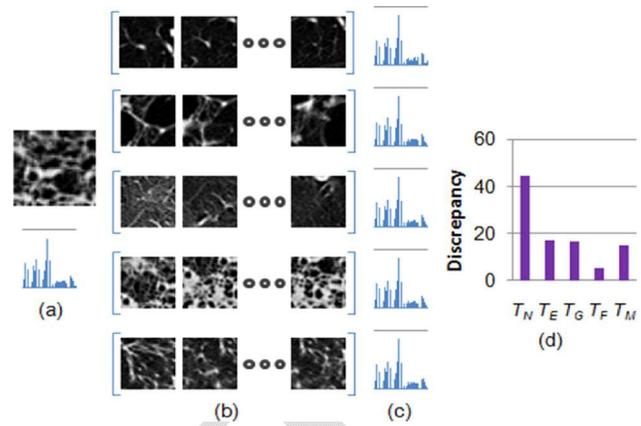


Fig. 5. Illustration of the proposed approximate patch classification. (a) An image patch P of category T_F , $f(P)$ and its feature descriptor with x -axis as the feature dimension and y -axis as the feature value. (b) The feature dictionary D constructed for each tissue category, with rows from top to bottom showing tissue categories T_N, T_E, T_G, T_F and T_M . (c) The approximated features $f_i'(P)$ from the corresponding dictionaries D . (d) Measure of discrepancy between the approximated features and the original feature vector, and the image patch P is thus labeled as T_F .

4.2.3. Labeling:

As the feature computation and approximation are designed at image-patch level, an AROI containing multiple image patches would sometimes exhibit a mixture of labeling of tissue categories.

It is necessary to perform a region-level classification to achieve a unanimous label for each AROI, based on collective **probabilistic estimation** of its image patches.

An AROI comprising A image patches is denoted as $AROI = \{P_a : a = 1, \dots, A\}$. With the patch-wise labeling $L(P_a)$ obtained from the approximate approach, we would then like to obtain a single label for the AROI

$$L(AROI) \in \{T_N, T_E, T_F, T_G, T_M\} \tag{2}$$

Rather than using a discrete labeling, five probability values are computed for each image patch P_a , representing the probabilities of P_a belonging to each tissue category. The probability value $P R (P_a, l)$ is derived based on the discrepancy between its feature vector and the approximation.

$$PR(P_a, l) = \frac{\exp(-2\|f(P_a) - f_l'(P_a)\|_2)}{\sum_{l' \in \{T_N, T_E, T_F, T_G, T_M\}} \exp(-2\|f(P_a) - f_{l'}'(P_a)\|_2)} \tag{3}$$

where $l' = \{T_N, T_E, T_F, T_G, T_M\}$. Then, the final labeling $LAROI$ is thus the category with the highest total probability from all image patches

$$L_{AROI} = \underset{l}{\operatorname{argmax}} \quad \text{_____} \quad (4)$$

V. DATASET AND EVALUATION

The publicly available database of ILD cases is used in this study. The database contains 113 sets of high-resolution CT (HRCT) images with 512 x512 pixels per slice. The database also indicates 2062 2-D AROIs that are manually drawn by two radiologists with 15 and 20 years of experience.

For each AROI a tissue pattern annotation is provided, with altogether 17 different tissue patterns. Among these, five commonly seen tissue patterns-normal, emphysema, ground glass, fibrosis, and micro nodule are studied by the researchers who create the database.

We thus focus on differentiating between these five tissue patterns in our study, involving 1458 AROIs from 95 image sets. A summary of the dataset is listed in Table I.

Table I. Summary of the Dataset Used

Tissue Category	Images	AROs	Patches
Normal(T_N)	15	157	6934
Emphysema(T_E)	9	108	1474
Ground glass(T_G)	35	416	2974
Fibrosis(T_F)	35	479	4456
Micro nodule(T_M)	18	298	7893

Note that one image set might contain multiple types of tissue patterns, and hence the sum of images of the five categories is larger than the actual number of images.

VI. 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 micro nodules—that is 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.

Finally, a single labeling is assigned for each AROI based on collective probabilistic estimation. Using a publicly available ILD HRCT image database, we have to conduct extensive experiments to evaluate the overall method design and the proposed feature descriptors and sparse-based classification, and demonstrated promising performance improvements.

We also suggest that the proposed method, in its whole or some components, can be easily extensible to other medical imaging domains. In our future work, we will further investigate more robust techniques of parameter selection for the feature set other than the current default settings, and more adaptive ways of reference dictionary construction other than the current concatenation using 1/3 of the database.

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