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Enhanced Image Patch Approximation For Lung Tissue Classification Using Feature Based Extraction

S.P.Kamalapriya	ME (CSE), Nehru Institute of Technology, kaliyapuram, Coimbatore - 641105
S. Pathur Nisha	ME (Ph D), Nehru Institute of Technology, kaliyapuram, Coimbatore - 641105
V.S.Thangarasu	ME.Ph.D,VSB engineering college,Karur. Ph:9444021802

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.

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). 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. It is thus suggested that an automatic system for differentiating the tissue patterns would be useful to provide initial screening or second opinions.

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

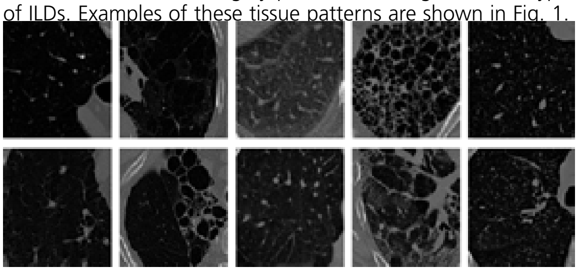

Fig.1 Five categories of Lung Tissues –normal, emphysema, ground glass, fibrosis, and micronodules

EXISTING METHOD

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. The 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.

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 discriminant 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

PROPOSED METHOD

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-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.

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: 1) the image patch labeling is enhanced with a statistical measure of the sparse coefficients to measure the minimum discrepancy; 2) 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; 3) a feature-space weighting scheme is designed based on overlapping of feature distributions for feature distance computation.

Third, the labeling of the annotated ROI (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

The original definition is extended to arbitrary circular neighborhood

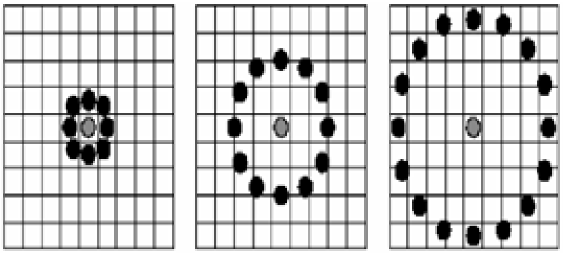

Fig2. P=8,R=1. P=12,R=2.5 P=16,R=4.0

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),M CHOG(P)}

where S= number of scales

K=cells for feature computation

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.

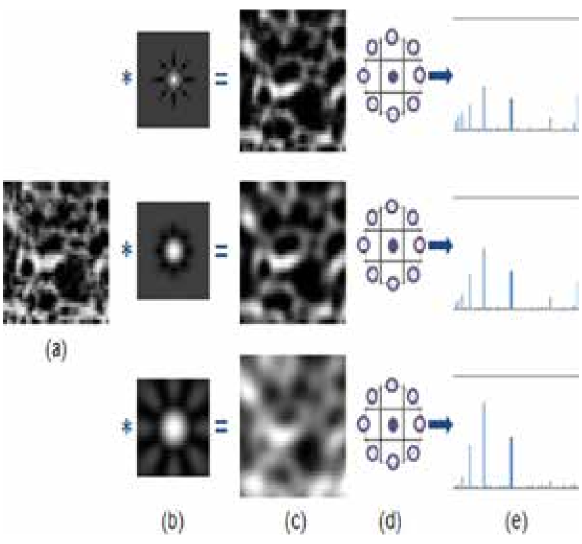

Fig. 3 . Illustration of the proposed RGLBP texture descriptor. (a) An image patch. (b) Rotation-invariant Gabor filter bank with three scales. (c) The Gabor filtered images. (d) Structure of LBP with radius 1 and 8 neighboring pixels.(e) The derived rotation-invariant histogram for each scale, with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

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 $PR(P_a, l)$ is derived based on the discrepancy between its feature vector and the approximation.

$$PR(P_{a,} l) = \frac{\exp(-2\|f(P_a)-f_1{'}(P_a)\|_2(_l)}{(f(P_a)-f_l{'}(P_a)\|_2(_l{'})}$$

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

LAROI = argmax

l

EVALUATION DATASET

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 also focus on differentiating between these five tissue patterns in our study, involving 1458 AROIs from 95 image sets.

TABLE1.SUMMARYOFDATASETS USED

Tissue Category	Images	AROIs	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
Micronodule(T_M)	18	298	7893

CONCLUSION

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 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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