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A GENETIC ALGORITHM BASED APPROACH FOR LUNG TISSUE CATEGORIZATION WITH FEATURE BASED IMAGE PATCH

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ABSTRACT

The interstitial lung disease (ILD) represents a group of more than 150 disorders of the lung parenchyma. Most of these cause progressive scarring of lung tissues and eventually affect breathing. Efficient categorization of lung tissue which is critical for identify the actual type of interstitial lung disease. From the HRCT image of lung, noise is removed by using wiener filter and then feature descriptors are used to extract a set of texture, intensity and gradient features from the image, for this Grey level co occurrence matrix (GLCM) and Gabor wavelet is used. A bank of Gabor wavelet with different scales and orientations is generated and images are filtered with convolution mask. Feature weighting and genetic algorithm are used as an intermediate step towards feature selection. Genetic algorithms are used to find the optimal set of weights and Feature weighting that improves the similarity based selection. Features are coded onto chromosomes in a novel way which allows weighting information regarding the features to be directly inferred from the gene values. Each image patch is then labeled based on its feature approximation from reference image patches as one of the tissue category as normal, emphysema, ground glass, fibrosis or micro nodule using patch-adaptive sparse approximation method.

KEYWORDS: Feature Extraction, Grey level co occurrence matrix, Gabor wavelet, Sparse classifier

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INTRODUCTION

Different ILDs normally exhibit different combinations of tissue patterns on HRCT images. Interpreting the HRCT images for lung diseases is challenging even for trained radiologists. Patients have different physical conditions and medical histories; hence even those with the same type of ILD could display quite different tissue patterns. So an automatic system for differentiating the tissue patterns would be useful. This project focus on classification of five categories of lung tissues on HRCT images-normal, emphysema, ground glass, fibrosis, and micronodules, which are highly prevalent among the main types of ILDs. 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. Therefore, a region-level classification is performed to achieve a unanimous label for each AROI, based on collective probabilistic estimation of its image patches.

In general there are perceivable visual distinctions between different tissue categories, the visual distinctions between different tissue categories sometimes subtle, and the pattern variations within the same tissue category are rather obvious. Therefore, it is quite challenging to design a robust method for automatic classification, accommodating both low inter-class distinctions and high intra-class variations a parametric modeling of the feature space separation, such an approach is more data-adaptive and is thus able to accommodate the intra-class feature variations well. The 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. It is highly possible to achieve even better results by enhancing the descriptor designs based on medical imaging characteristics.

RELATED WORKS

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.

Visual features of lung tissues can be extracted by rotation invariant Gabor-local binary patterns (RGLBP), multi-coordinate histogram of oriented gradient (MCHOG) [8].

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Run length (RLE) [10] have also been widely incorporated for getting additional feature information. Another type of popular feature extraction techniques is based on filters, like Gaussian [3].

Once the feature descriptors are derived, 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 [3], Support vector machine (SVM) [4], Linear discriminant analysis (LDA) [1], Bayesian classifiers [10], and Artificial neural network (ANN) [9]. 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. PASA does not involve discriminative learning like SVM; it can be actually more discriminative with its non-parametric formulation. Without requiring

PROPOSED DESCRIPTION

Interstitial lung disease (ILD) represents a group of more than 150 disorders of the lung parenchyma. 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.

From the HRCT image of lungs noise is removed by using wiener filter, to get enhanced image. 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 T-I-G feature set, combining texture, intensity and gradient features are extracted for each image patch, by using Gabor wavelet and Grey level co-occurrence matrix. Genetic algorithm is used for feature selection. Genetic algorithm (GA) is employed to search for the optimal set of weights. Then the image is classified into any one of tissue class (Normal, Emphysema, Ground glass, Fibrosis, and Micronodules) by the spare classifier by using a set of reference images. Spare classifier quite effective in handling intra-class variations, with classification based on reference samples rather than learned parametric models.

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ARCHITECTURE

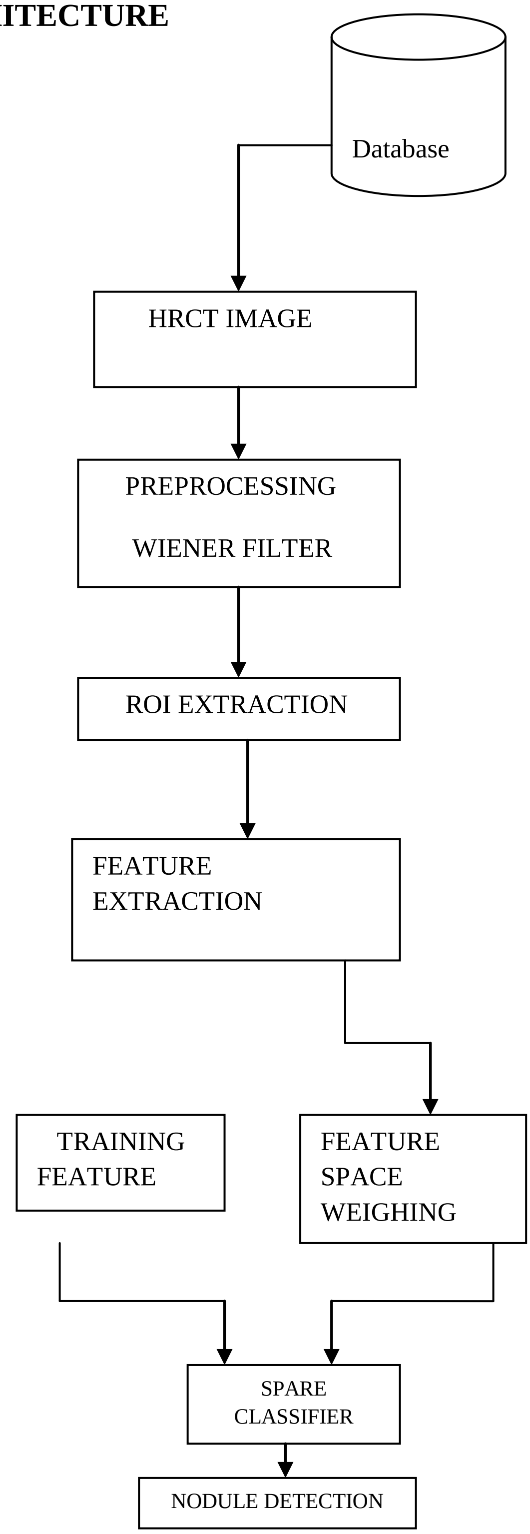

Fig: System Design

In terms of computational complexity, compared to SVM, PASA has lower training costs, only requiring construction of reference dictionaries PASA classify an image patch based on the closeness of approximation by other image patches from each tissue category.

Image Preprocessing

In order to remove noise and artifacts Wiener filtering technique is applied as preprocessing step of noise reduction and isolation. Wiener filter provides the best restored signal with respect to the square error averaged over the original signal and the noise among linear operator.

Feature extraction

For feature extraction grey level co-occurrence matrix (GLCM) and Gabor wavelet is used. The matrix contains the conditional joint probabilities of all pair wise combinations of gray levels given two parameters: inter pixel distance and inter pixel orientation. Gabor wavelet can also decompose the image into components corresponding to different scales and orientations. Gabor filters achieve optimal joint localization in spatial and spatial frequency domain.

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Feature space weighing

For feature selection and feature weighing genetic algorithm is used.. Genetic Algorithm (GA) is employed to search for the optimal set of weights. Each candidate set of weights W = {w1, w2,...,wD}, a codebook C(W) is computed and the whole database labeled according to W and C(W). Then, c (k, i) and c (i) are counted for each training subset U (i), and the speaker models are estimated. Finally, utterances in the validation set V={V(1),V(2),…,V(S)} are classified, and the classification accuracy used as fitness function. Once all the candidates are evaluated, some of them (usually the fittest ones) are selected, mixed and mutated in order to get the population for the next generation.

Sparse classifier

Sparse classifier is designed to classify an image patch p based on the closeness of approximation by other image patches from each tissue category. Denoting the five tissue categories—normal, emphysema, ground glass, fibrosis, and micronodule—as the objective here is to assign each image patch p a category label 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. Feature space weighting scheme is designed based on overlapping of feature distributions for feature distance computation. The performance of tissue classification is measured by recall, precision and F-score

$$\text{Recall} = \frac{TP}{(TP+FN)}$$

$$\text{Precision} = \frac{TP}{(TP+FP)}$$

$$\text{F-score} = \frac{2TP}{(2TP+FN+FP)}$$

where TP, FN, and FP are the numbers of true positive, false negative and false positive classifications of tissue categories

Performance evaluation

In the performance evaluation, we compare the Existing feature descriptors that is rotation invariant gabor local binary patterns (RGLBP), multi-coordinate histogram of

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oriented gradient (MCHOG) with grey level co-occurrence matrix (GLCM) and Gabor wavelet.

ANALYSIS

Interstitial lung diseases cause progressive scarring of lung tissues and eventually affect breathing. Lung tissue categorization 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. From the HRCT image of lung, noise is removed by using wiener filter and then feature descriptors are used to extract a set of texture, intensity and gradient features from the image, for this Grey level co occurrence matrix (GLCM) and Gabor wavelet is used. Then the input image is classified as any one of the tissue category by the spare classifier. Classification is accurate with large margins, for this confidence of prediction (CoP) measure is used for an image patch p. Confidence of prediction is the difference between the probability estimates of the expected tissue category and the category with the highest labeling probability. With this measure, CoP (p) less than zero means image patch is mislabeled, and a large positive implies a large confidence level of labeling.

CONCLUSION

Early detection of interstitial lung disease is vital for treatment. The input HRCT image of lungs is classified based on the texture, intensity and gradient features extracted. Classification accuracy is improved by using more robust techniques for feature extraction.

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