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Classification of Diffuse Lung Diseases Patterns by a Sparse Representation Based Method on HRCT Images

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***Abstract*— This paper describes a computer-aided diagnosis (CAD) method to classify diffuse lung diseases (DLD) patterns on HRCT images. Due to the high variety and complexity of DLD patterns, the performance of conventional methods on recognizing DLD patterns featured by geometrical information is limited. In this paper, we introduced a sparse representation based method to classify normal tissues and five types of DLD patterns including consolidation, ground-glass opacity, honeycombing, emphysema and nodular. Both CT values and eigenvalues of Hessian matrices were adopted to calculate local features. The 2360 VOIs from 117 subjects were separated into two independent set. One set was used to optimize parameters, and the other set was adopted to evaluation. The proposed technique has a overall accuracy of 95.4%. Experimental results show that our method would be useful to classify DLD patterns on HRCT images.**

I. INTRODUCTION

Diffuse lung diseases (DLD) include many abnormality that spread out in large areas of lung. The high-resolution CT (HRCT) is able to provide an accurate assessment of pulmonary patterns, so it has been considered to the most important modality for diagnosis of DLD in recent years. However, the diagnosis of DLD on HRCT images is a difficult task for radiologists. There is not an objective identification of pulmonary patterns in clinical protocols, and the interpretation of HRCT images depends on radiologists' experiences. Besides, the huge number of CT slices make a big burden on radiologists. Therefore, a computer-aided diagnosis (CAD) tool is required to provide the radiologists with a "second opinion" for the diagnosis of DLD.

In the past ten years, many CAD systems have been developed to automatically analyze and classify DLD patterns. Most conventional methods paid attention to design discriminative features, such as topological texture features [1], statistical texture features [2] and local binary patterns [3]. Although the texture features have excellent performance on CAD of DLD, it is still difficult to classify pulmonary patterns with inhomogeneous texture. Therefore, the geometrical information is often adopted to design more powful features combined with texture features. In published work [4], the pulmonary patterns were determined by six kinds of physical measures, three on CT values (mean and standard deviation of CT values and air density components) and three on geometric information (nodular components, line components and multilocular components).

To improve the performance of classifying DLD patterns, researchers also employed clustering methods to generate discriminant features, for example, the cluster-based signature-matching [5]. Assuming that the same types of cases have similar distribution of local features, the unique signature of VOI is defined as the centroid and histograms of clusters constructing by k-means. And the earth mover's distance (EMD) approach is applied to measure the similarity between two signatures. In order to save computing cost, the signatures of cases with the same class are re-clustered to generate a canonical signature. So the signatures of testing VOIs can be compared with canonical signatures instead of all training signatures in the classifier. Although the clustering of features has potential to accurately describe the difference between DLD patterns, the performance of classification would be affect by the accuracy of clustering method.

Recently more and more researchers have reported that the sparse representation based approaches can be successfully applied in the CAD [6, 7]. The main idea of sparse representation is to approximate samples by a linear combination of little number of key features (atoms) selected from an overcomplete dictionary with a lower re-construction error. The overcomplete dictionary allows a flexible representation of samples. So the important information can be captured from the samples while discarding irrelevant details. Besides, the image patches can also be seemed as sparse signals [8]. In this paper, we combined local features and a sparse-representation model to classify normal tissues (NOR) and five types of DLD patterns including consolidation (CON), ground-glass opacity (GGO), honeycombing (HCM), emphysema (EMP) and nodular (NOD). Fig. 1 illustrates the images of six types of pulmonary patterns. According to our knowledge, there is no work to combine local features and sparse representation on analyzing DLD patterns. Comparing to the work published in [6], which also applied a sparse-representation model to analyze DLD patterns, the main differences are listed as follows: 1. More kinds of pulmonary patterns; 2. 3D VOIs instead of 2D ROIs; 3. Local features based on CT values and eigenvalues of Hessian matrix; 4. Different method of generating image descriptors for classification.

II. METHOD

We proposed a sparse representation based method to classify six types of pulmonary patterns on HRCT images.

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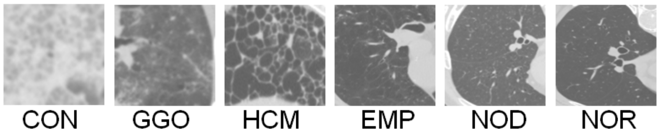

Fig. 1. Example of six pulmonary patterns in HRCT: consolidation(CON), ground-glass opacity(GGO), honeycombing(HCM), emphysema(EMP), nodular(NOD) and normal tissue(NOR)

Fig. 2 gives the framework of proposed method. Firstly, the local features were extracted from the VOIs. Secondly, in the sparse-representation model, an overcomplete dictionary was learned using the feature vectors from the training data, and the descriptors were generated as the input of classifier according to the dictionary and original feature vectors. Finally, the descriptors of six types of pulmonary patterns were recognized by a SVM classifier.

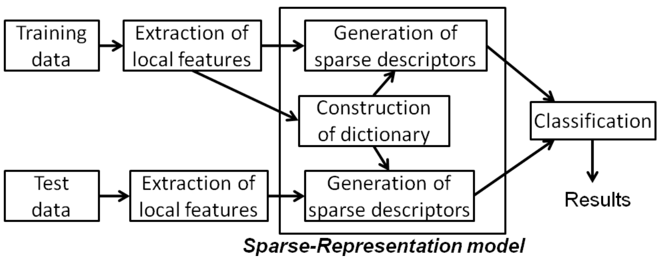

Fig. 2. The framework of proposed method;

A. Extraction of local features

From Fig. 1, it can be found that the NOD and HCM are mainly characterized by 3D shape-information, and the CON and EMP are featured by CT values. Considering that the eigenvalues of Hessian matrix have been used to represent the shape of objects [9], it was adopted to compute the local features with CT vales in the research. The calculation of local features is illustrated in Fig. 3. Firstly, a cube-shaped patch was generated at each sampling point of VOI, and the center of patch was located at the sampling point. Secondly, in order to analyze the geometric information of patterns, the eigenvalues of Hessian matrix were calculated on each voxel within the patches. Let $\lambda_1, \lambda_2, \lambda_3$ be the eigenvalues of Hessian matrix. The eigenvalues were arranged in a descending order ($\lambda_1 \geq \lambda_2 \geq \lambda_3$) and formed three new patches. Finally, four kinds of statistical measures were calculated on the four patches: mean, standard deviation, skewness and kurtosis. In experiments, the step of sampling points and the size of VOIs were set to 4×4×4 and 32×32×32 respectively. So there are 9×9×9=729 sampling points in one VOI. The size of patch is a parameter, which was optimized in experiments.

B. Sparse-Representation Model

After extracting local features, we adopted a sparse-representation model to generate descriptors as the input of classifier. Given m feature vectors $\boldsymbol{y} \in \mathbb{R}^n$ and the corresponding representation coefficients $\boldsymbol{a} \in \mathbb{R}^k$. The collection of m feature vectors and representation coefficients form two

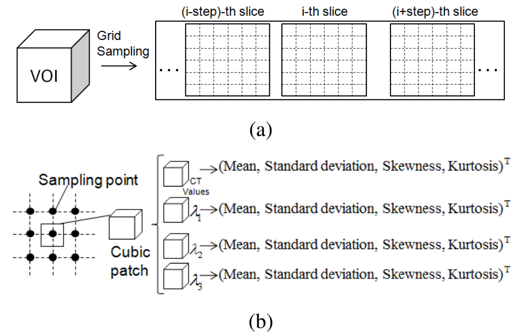

Fig. 3. The four extraction of local features (a) Grid sampling on the VOIs; (b) Calculating 4 statistical measures on each patch.

data matrix $\boldsymbol{Y} \in \mathbb{R}^{n \times m}$ and $\boldsymbol{A} \in \mathbb{R}^{k \times m}$ respectively. Let $\boldsymbol{D} \in \mathbb{R}^{n \times k}, n \ll k$ be an overcomplete dictionary matrix, the sparse representation can be formulated as

$$\min_{\boldsymbol{y}} ||\boldsymbol{y}||_0 \quad subject\ to ||\boldsymbol{Y} - \boldsymbol{D}\boldsymbol{A}||_2^2 \leq \varepsilon \tag{1}$$

where the $||.||_0$ means the sparsity of coefficient (number of non-zero entries in the vector).

In this work we adopted the K-SVD algorithm to learn the dictionary because of its simplicity and highly efficiency [10]. Starting from initializing by a random dictionary matrix with normalized atoms, the dictionary is learned by iterative optimizing the coefficients (with dictionary fixed) and updating dictionary (with coefficients fixed), until $||\boldsymbol{Y} - \boldsymbol{D}\boldsymbol{A}||_2^2 \leq \epsilon$. In the stage of optimizing the coefficients, it is suggested to use a pursuit algorithm. We adopted the default solver in K-SVD, Orthogonal Matching Pursuit (OMP) in this research [11]. In the stage of updating the dictionary, the columns of dictionary matrix (atoms) are sequentially modified and normalized while keeping other atoms fixed. To update the atom d_i, firstly the error matrix $\boldsymbol{E}_i$ is calculated

$$\boldsymbol{E}_i = \boldsymbol{Y} - \boldsymbol{D}\boldsymbol{A} + \boldsymbol{d}_i \boldsymbol{a}_T^i \tag{2}$$

where $\boldsymbol{a}_T^i$ is the i-th row of $\boldsymbol{A}$. Secondly, the group of examples using the atom d_i are found. Defining $\omega_i = \{j | 1 \leq j \leq m, \boldsymbol{a}_T^i(j) \neq 0\}$, the error matrix is restricted by selecting the columns corresponding to the ω_i. Finally, the singular value decomposition (SVD) is adopted to decompose the restricted error matrix

$$\boldsymbol{E}_i^R = \boldsymbol{U} \boldsymbol{\Delta} \boldsymbol{V} \tag{3}$$

and the atom d_i is updated by $\boldsymbol{u}_1$.

Using the dictionary, the original local features were represented by the corresponding sparse coefficient vectors, the same with the sparse coding stage in learning dictionary. We also adopted the OMP in this step. Then a spatial "pooling" was performed to combined the representation coefficients from same VOI into a descriptor vector. The descriptors should preserve important information of VOIs while missing irrelevant details. Two popular choices, the max pooling and average pooling were considered in this research. In the sparse-representation model, the number of atoms and sparsity of coefficients are two parameters determined by experiments.

C. Classification

Finally the descriptors generated by the sparse-representation model were classified by a SVM classifier. We used a version named LIBSVM [12]. Considering that the classification based on linear kernel can achieve a competitive performance and lower computation cost than the nonlinear kernels in the sparse representation [8], the LIBSVM was employed with a linear kernel. The kernel is defined by Eq.4

$$Linear\ kernel: \quad K(x_i, x_j) = x_i^T x_j \tag{4}$$

where x_i and x_j are both descriptors. One of the most popular techniques, one-against-other was applied by LIBSVM to extend the binary SVM classifier for the solution of multi-class tasks [13]. The classifier has one parameter: soft-margin penalty *C*. We optimized the parameter in the training stages.

III. EXPERIMENTS AND RESULTS

A. Data

We obtained 117 scans from 117 subjects from our cooperative hospital. All scans were acquired by Toshiba Aquilion 16-row multi-slice CT when edge-enhanced filtering was not applied. A tube voltage of 120kVp and current of 250mAs were used. The resolution of scans is 512×512, and the in-plane resolution is about 0.6mm. The slice thickness is 1mm. The scans were reviewed by three experienced radiologists, and the VOIs were constructed according to the following procedure: 1. One radiologist was asked to review all scans, and a maximum of three axial slices from each scan were selected. Only one type of pattern dominantly exists on the selected slice. 2. The other two radiologists were asked to review the results of the first radiologists again, and saved agreed slices for the next step. 3. All three radiologists were asked to marked the regions of patterns on the selected slices respectively. 4. The common regions marked by all three radiologists were extracted. 5. The grids with a size of 32×32 were overlaid on the determined regions, and square-shaped patches were built. For patches with five DLD patterns, the specific type of pattern should spread out in a minimum of 70% of total area. 6. The 32×32×32 VOIs were constructed according to the patches. The patches were treated as the central-axial slice of VOIs.

In the experiment, we divided the VOIs into two sets nearly in half. One set was adopted as the training data set, which was used for tuning parameters. The other set was employed to evaluate the performance. There is no cross-subject in the two sets. Because the area of pulmonary patterns marked by radiologists on the slices are not the same, the number of VOIs of the same pattern in the two sets would be different. The number of VOIs of each type of patterns for training and test data are summarized in Table I.

TABLE I
NUMBER OF VOIS IN THE TRAINING AND TEST SET.

	Training data	Test data
CON	49	45
GGO	170	160
HCM	221	204
EMP	323	275
NOD	113	92
NOR	435	273
Total	1311	1049

B. Experimental Setting

For the proposed method, there are mainly four kinds of parameters optimized in the training stage: the size of cube-shaped patches, the number of atoms and the sparsity of coefficients, and the parameter related to the classifier. We tuned the values of patch size from 2×2×2 to 3×3×3 with a step of 1×1×1, the number of atoms from 500 to 3000 with a interval of 500, and the sparsity from 2 to 14 with a step of 2. All of these parameters were optimized simultaneously by a 20-fold cross-validation test on the training set. Then the proposed method with the determined parameters was evaluated on the test set.

The proposed method was compared with two kinds of state-of-the-art baseline methods, which was called SpeDesFea [4] and CanSigEMD [5] respectively in this paper. The way of tuning parameters was the same with the proposed method.

- **SpeDesFea** The pulmonary patterns were recognized by six types of specially designed features, including mean and standard deviation of CT values, air density components, nodular components, line components and multilocular components. An three-layered artificial neutral networks (ANN) with back-propagation algorithm was adopted as the classifier. The implementation of this method was the same as [4].
- **CanSigEMD** This method applied the k-means algorithm to calculate clusters' centers of each VOI, and the EMD method was used to measure the similarity between the signatures. The nearest neighbor (NN) was adopted as the classifier. The CanSigEMD has only one parameter, the number of clusters. Because it is suggested to avoid too large value, we tried the number of clusters from 10 to 50 with a interval of 10.

C. Results and Discussion

The overall accuracies of three kinds of methods are summarized in Table II. It can be seen that the proposed method provides the best overall accuracy of classification. Table III gives the statistical differences between the proposed method and baseline methods by McNemar's test. All of the *p* values are less than 0.00001. Fig. 4 compares the recognition of each pulmonary pattern by the three methods. The classification of texture-based patterns is relatively better than shape-based patterns by the two baseline-methods. For the SpeDesFea method, we thought it may attribute to the results of detecting nodular, linear and multilocular component, which is a significant important and difficult work in the CAD. In the CanSigEMD method, only CT value was considered in the calculation of features. So the shape-based patterns may be confused with texture-based patterns. Besides, the accuracy of k-means would affect the recognition of pulmonary patterns. By the proposed method, the recognition rates of all patterns are higher than 90%. It is demonstrated that the proposed method is able to well recognize both texture-based patterns and shape-based patterns. Table IV gives the confusion table of proposed method. We considered there may be two reasons. First, we compute the local features on CT value and eigenvalues of Hessian matrices, which can well represent the textural and geometrical information of pulmonary patterns. Second, by the sparse-representation model, the descriptors can retain crucial information of local features while discard the irrelevant details. So it is able to better describe the distribution of local features.

TABLE II

COMPARISON OF THREE KINDS OF METHODS

Method	Accuracy
Proposed method	95.4%
SpeDesFea	75.1%
CanSigEMD	64.8%

TABLE III

STATISTICAL DIFFERENCES BY MCNEMAR'S TEST

Methods	p value
Proposed method vs SpeDesFea	< 0.00001
Proposed method vs CanSigEMD	< 0.00001

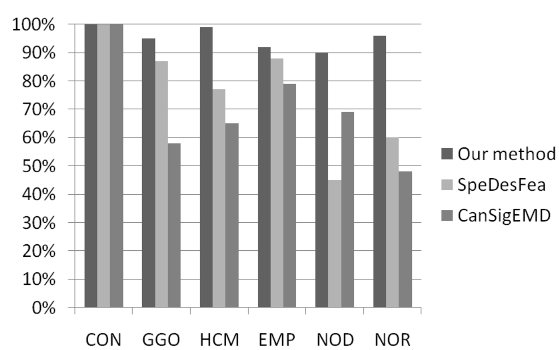

Fig. 4. Recognition of six kinds of pulmonary patterns by the three methods

TABLE IV

CONFUSION TABLE OF PROPOSED METHOD

	Estimated Types						
True Types	CON	GGO	HCM	EMP	NOD	NOR	Sensitivity
CON	45	0	0	0	0	0	100%
GGO	0	152	0	1	7	0	95.0%
HCM	0	1	203	0	0	0	99.5%
EMP	0	0	1	255	2	17	92.7%
NOD	0	3	0	0	83	6	90.2%
NOR	0	2	0	2	6	263	96.3%
Precision	100.0%	96.2%	99.5%	98.8%	84.7%	92.0%	

IV. CONCLUSIONS

In this research, we proposed a sparse representation based method to classify six types of pulmonary patterns. The sparse-representation model composed of three steps: dictionary learning, sparse coding and spatial pooling. After extracting the local features, the dictionary was learned by performing the K-SVD and OMP iteratively until the reconstruction error smaller than the stopping ruler. Then the original local features were represented by OMP using the learned dictionary. Finally, the spatial pooling was adopted to combined the representation coefficients of same VOI into a descriptor as the input of a SVM classifier. The proposed method has a overall accuracy of 95.4%, and the recognition rates of all patterns are higher than 90%. Experimental results show that our method is superior to other two baseline methods. We will try other sophisticated features and sparse coding methods in future research.

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