Computational Texture Analysis in Interstitial Lung Disease: Comparison of Descriptors and Classification Accuracy

Poster No.: C-2344
Congress: ECR 2013
Type: Scientific Exhibit
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Keywords: Lung, Computer applications, CT-High Resolution, CAD, Tissue characterisation
DOI: 10.1594/ecr2013/C-2344

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Purpose

Interstitial Lung Disease (ILD) can be characterized by evaluation of tissue alterations which can be seen as textures in High Resolution Computer Tomography (HRCT) images. About 200 subentities of ILD are known and are classified in clinical practice with often confusing classification schemes [5]. Several automatic lung texture classification systems have been developed in the last years [8] to overcome this problems. The aims of automatic lung texture classification can be summarized as following:

- Automatic classification (quantification and localization) of tissue alterations seen as textures in HRCT images.
- Use the measured distribution of tissue alteration to model and predict underlying diseases.
- Standardize the nomenclature of tissue alterations seen in HRCT images.

Contributions

All proposed systems concentrate on lung texture analysis. However, a direct comparison of the approaches is difficult because they are tested in different settings and datasets. This work concentrates on the following aims:

1. Test the overall classification performance of several texture features which are used in literature and directly compare them on one and the same dataset.
2. Identify difficulties in classifying specific texture classes and the confusion with other classes. Some texture classes may be confused by an automatic classifier (as well as by a human expert) because they have too similar appearance.

Methods and Materials

Dataset

The data is part of the TALISMAN dataset [2] of the University of Geneva including 97 HRCT images of the lung. The images show cases that have a proofed relation to ILD. Five tissue patterns are annotated by two radiologists to serve as a groundtruth for the automatic classification system. The tissue patterns are normal, emphysema, ground glass, fibrosis and micronodules. Example images are shown in Fig. 1 on page 3.

Method
The automatic classification system is build around a Random Forest Classifier [1]. The five low-level texture features Gray Level Histograms (GLH) [3], Haralick features [4], Local Binary Patterns (LBP) [7], Gaussian Filterbank [9] and Riesz features [3] are compared. This low-level features are further compared in two different settings:

- As local **voxel features**. Voxel features describe the texture in a defined, local neighborhood of an image voxel.
- And as **region features**. Region features are based on the Bag-of-Features paradigm [6]. A superpixel algorithm [10] partitiones the images automatically in regions of homogenous texture. Then prototypes of textures are learned in an extra training step. Regions are represented as histograms of the learned prototypes.

Images for this section:

![Images of tissue patterns](image1)

**Fig. 1**: Example images of the five tissue patterns that are automatically classified in this work. All patterns have a relation to Interstitial Lung Disease.
Results

The classification performance (Fig. 2 on page 4) shows that Haralick and Riesz +GLH features are better suited for the use as voxel features, whereas GLH, Gaussian Filterbank and LBP features have better performance when used as region features. LBP show low performance when used as voxel features. However, it is the best performing region feature set and can compete with Haralick features (the best voxel feature set).

Fig. 3 on page 5 depicts example classification result images for Haralick and LBP features as both, voxel and region features. Examples are shown for all five texture classes and together with the groundtruth at the left side of the figure. Note the noisy output of the LBP features in voxel classification. The contrast to the Haralick features in voxel classification is obvious. Whereas in region classification the LBP features seem to provide a comparable and even smoother output than the Haralick features.

The classification system labels about 70% of all samples correct. However, the rest of the texture samples are confused with a wrong class. Fig. 4 on page 6 depicts selected images patches that are classified with the help of region features. Correct and confused examples are shown in a matrix of images. Correct class labels can be seen on the left, the classifier's predicted label on the top. The classified regions in the image patches are marked with outlines. Correct classified patches are outlined in color and are located in the diagonal of the matrix. The image examples in the columns (the classifier's class label) have similar appearance, although they have different groundtruth labels. However, the reason of this behaviour may be found in a large inter-class variation of the groundtruth labels, rather than in low classification performance.

Images for this section:
Fig. 2: Classification performance (percentage of correct classifications) of five texture feature methods. Texture features are used as voxel features (black) and region features (white).

Fig. 3: Output of the classification system for Haralick and LBP features for all five texture classes. The leftmost image column shows the groundtruth created by radiologists. The
second and third image column show voxel classification results and the fourth and fifth column show region classification results.

**Fig. 4:** Classified image patches are shown. The classified regions are marked with outlines. Correct classified patches are outlined in colour and are located in the diagonal of the matrix. The location of the images in the matrix reveals the class labels. Class labels of radiologists (groundtruth) are printed on the left side of the matrix, the classifier's prediction can be found on top of the matrix.
Conclusion

All five texture features tested are feasible for lung texture classification in either a voxel or region feature setting. When texture features are used as region features, the typical appearance of textures occurring in the data can be learned. The application of region features leads to outstanding classification performance of the computationally very efficient LBP features. Additionally, patterns with high intra-class variations (as the normal pattern) can be better discriminated with the help of learned prototypes of the region features. This makes LBP in a region feature setting to the preferable choice in lung texture classification.

References


Personal Information