Computerized Medical Imaging and Graphics 40 (2015) 39–48

Contents lists available at ScienceDirect

Computerized Medical Imaging and Graphics

journal homepage: www.elsevier.com/locate/compmedimag

A new classifier fusion method based on historical and on-line classification reliability for recognizing common CT imaging signs of lung diseases

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ARTICLE INFO

Article history:
Received 4 April 2014
Received in revised form 3 September 2014
Accepted 3 October 2014

Keywords:
Medical image classification
Classifier fusion
Lung CT images
Common CT imaging signs of lung diseases (CISL)
Confusion matrix

ABSTRACT

Common CT imaging signs of lung diseases (CISL) play important roles in the diagnosis of lung diseases. This paper proposes a new method of multiple classifier fusion to recognize the CISLs, which is based on the confusion matrices of the classifiers and the classification confidence values outputted by the classifiers. The confusion matrix reflects the historical reliability of decision-making of a classifier, while the difference between the classification confidence values reflects the on-line reliability of its decision-making. The two factors are merged to determine the weights of the classifiers' classification confidence values. Then the classifiers are fused in a weighted-sum form to make the final decision. We apply the proposed classifier fusion method to combine five types of classifiers for CISL recognition, including support vector machine (SVM), back-propagation neural network (BPNN), Naïve Bayes (NB), *k*-nearest neighbor (*k*-NN) and decision tree (DT). In the experiments on lung CT images, our method not only brought stable improvements of recognition performance, compared with single classifiers, but also outperformed two well-known methods of classifier fusion, AdaBoost and Bagging. These results show that the proposed method is effective and promising.

1. Introduction

CT technology developed quickly from the conventional single-slice acquisitions to volume acquisition with multi-slice, hence, it contains more and more image information and can highlight the density difference between the normal and diseased lungs [1]. However, it is time-consuming for radiologists to identify a large number of abnormal lesions from the CT images. Therefore, the problem of recognizing lesions in lung CT images automatically for aiding radiologists in the diagnosis of lung diseases has received extensive attention in recent years.

Various types of single classifiers have been used in the past years for lung CT image recognition, including *k*-nearest neighbors (*k*-NN) [2–6], neural networks (NN) [5–10], Bayes [6,11,12], rule-based schemes [13], decision trees (DT) [6,11], linear discriminant analysis (LDA) [14] and support vector machine (SVM) [2,5,6,14]. Although much progress has been made, a single classifier is still difficult to achieve satisfactory performance in the practical applications. Plentiful studies have shown that the fusion of multiple classifiers is a feasible solution to bring the better classification results since diversity of classifiers usually compensates for errors of any single classifier.

In this paper, we propose a novel weighted-sum method of classifier fusion for recognizing common CT imaging signs of lung diseases (CISLs). Different from other weighted-sum counterparts, we consider both HIStorical reliability and ON-line reliability of each single classifier. The resultant method is accordingly called HISON for short. The historical reliability is reflected by the confusion matrix established in the training procedure and the on-line reliability is reflected by the difference between the classification confidence values computed in the test procedure. The two information above are employed to determine the weight of each single classifier. Then the classifiers are combined in the weighted linear sum form to make the final classification decisions. We apply the proposed HISON classifier fusion method to combine the five widely used classifiers, including support vector machine (SVM), back-propagation neural network (BPNN), Naïve Bayes (NB), *k*-nearest neighbors (*k*-NN) and decision tree (DT), for recognizing

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http://dx.doi.org/10.1016/j.compmedimag.2014.10.001
0895-6111/

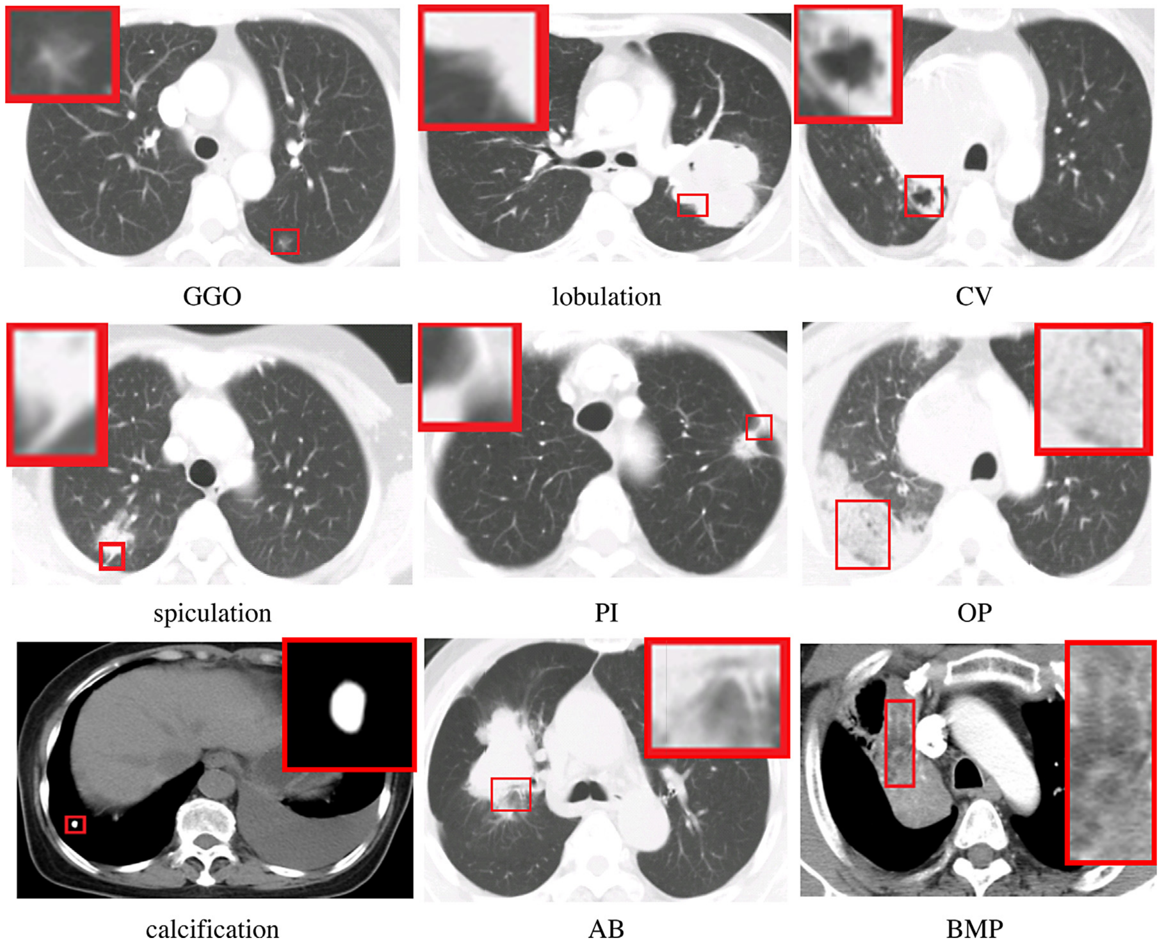

Fig. 1. The instances of nine CISL categories indicated by the rectangular boxes in lung CT images.

CISLs contained in the regions of interests (ROIs) in lung CT images. The resultant method was tested in the instances collected from the Cancer Institute and Hospital at Chinese Academy of Medical Sciences. The CISLs mean the well-known categories of CT imaging signs of lung diseases that frequently appear in patients' lung CT images and play important roles in the diagnosis of lung diseases. Nine categories of CISLs are considered in this paper, including grand grass opacity (GGO), lobulation, cavity & vacuolous (CV), spiculation, pleural indentation (PI), obstructive pneumonia (OP), calcification, air bronchogram (AB), and bronchial mucus plugs (BMP). We illustrate them in Fig. 1. Notice that this paper is expanded and updated from a preliminary study of ours [15]. More comprehensive investigation of related work and more in-depth theoretical analysis are provided. Furthermore, much more experiments have been designed and conducted to prove the effectiveness, the efficiency and the robustness of the proposed method.

The rest of this paper is organized as follows. Section 2 reviews the common related work on classifier fusion in the medical imaging community. Section 3 presents our classifier fusion method. Section 4 describes our CISL recognition algorithm. The experimental results are reported in Section 5. We conclude in Section 6.

2. Related work

The classifier fusion methods based on the linear sum have attracted a lot of attention for their simplicity and good performance. It can be divided into two types: hard classification based and soft classification based.

In hard classification based fusion methods, the output of each classifier is the class label, usually 1 for the recognized class and 0 for other classes. Based on this kind of outputs, the voting strategy is often used to realize the fusion. It counts the numbers of all categories classified by the classifiers and makes the class which receives the largest number votes among the voters, that are the classifiers, as the final classification decision, such as majority vote (MV), weight vote (WV), Learn^{++} and Bagging, and so on. Wang et al. [16] used the minimum within-class scatter support vector machine as the individual classifiers and made the decision for the classification of pulmonary cancer in CT scanned images by using the MV. Salama et al. [17] introduced a MV fusion method for combining the different classifiers including DT, multi-layer perception (MLP), NB, SVM, *k*-NN and tested the classification accuracy of the combined classifier on three different databases, Wisconsin Breast Cancer, Wisconsin Diagnosis Breast Cancer and Wisconsin Prognosis Breast Cancer. Lee et al. [18] combined LDA classifiers through using the MV method to make the diagnosis of pulmonary nodules. Prasad et al. [19] used the MV method to fuse LDA classifiers for classifying mammogram into malignant or benign. WV means that not all classifiers are equal and each classifier's vote carries the different weight. Soda et al. [20] applied the WV method to achieve the better results for the recognition of antinuclear autoantibodies (ANA). Patel et al. [21] combined several SVM classifiers using the WV method for early diagnosis of Alzheimer's disease, where the weights of SVMs were determined based on the average performance of classifiers on the validation data. Learn^{++} is an incremental learning algorithm and creates an ensemble of weak classifiers, each trained on a subset of the current training dataset.