Automated Lung Nodule Classification by Artificial Neural Network and Fuzzy Inference System

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***Abstract*—Lung cancer is the most cause of death from all cancers being less survival rate according to various online cancer societies. The former medical studies showed that the early diagnosis of lung cancer with screening program is the way to decline mortality rate. Radiological examination takes a tremendous time and need many medical experts having a large number of images per patient. Consequently, the accuracy of examination results mainly depends on the skills of physicians. Computer-aided Detection (CAD) in radiology can provide a functional and advantageous way to physicians aiming at improving accuracy and assisting in early detection of cancer, saving the time of radiologists in exam evaluation of cancers. Our proposed CAD system has fulfilled these all tasks combining image processing and Artificial Neuro-Fuzzy Inference System (ANFIS); with 98% sensitivity of finding true lung nodules, 94.4% sensitivity and 85% accuracy of removing false detectives, and 87% sensitivity and 78% accuracy for cancerous nodules detection.**

Keywords—ANFIS; CAD; Early Detection; False Positive Removal; High Sensitivity;

I. INTRODUCTION

Annually, at least 12 million of lung cancer patients have been diagnosed. Although lung cancer is the second leading cause of cancer comparing with other cancer types, it is the most causing death of cancer with 19.39% from all cancers based on the World Health Organization (WHO) data [1]. The performance of CAD system is assessed on sensitivity of the system. 100% sensitivity means the system can finds all true pulmonary nodules. Detection of true lung nodules is a challenge being complex anatomical structure of lungs, and composing with radiographic noise caused by electronic scanners. Lung nodules can be classified based on their shape, size, smoothness, and calcification. Generally speaking, a lung nodule has a round shape and a small nodule is hardly to become cancerous. Mostly, nodules whose margins are smooth, well-defined are benign while that of malignant nodules are thick and irregular. As the final stage of our CAD system, small nodules of 3-30mm are classified as cancerous or not by ANFIS classifier.

II. RELATED WORK

M. Tan et.al [2] proposed CADe (Computer-Aided Detection) system to classify nodules or non-nodules by genetic algorithms and Artificial Neural Network; with total of 360 nodules of 3-30 mm in diameter of 134 patients enrolled in LIDC society. This CADe system obtained 87.5% sensitivity with 4 FP (false positives) per scan. In [3], 420 CT scans of 420 patients, with 3-30 mm in diameter of 379 likelihood of malignancy, are randomly chosen from LIDC database, and 1,109 nodules were segmented by regions growing and watershed transform and then the true nodules are detected by rule based classifier, and the likely malignant nodules are classified by SVM classifier. This system obtained 97% accuracy for segmentation stage, 94.4% sensitivity with 7.04 FP per scan for CADe system, and 93.9 % sensitivity with 7.21 FP per case for classification stage.

III. PROPOSED SYSTEM'S PROCEDURE AND METHODS

In our proposed CAD system, we have used 617 nodules of 151 CT scans with 166 true lung nodules, and validated the segmented nodules with their ground truth, claimed by radiologists, in segmentation stage. After then, non-nodules are removed by ANFIS in CADe system. In CADx (Computer-Aided Diagnosis) system, the candidate lung nodules are also classified by ANFIS as cancerous (abnormal) nodules or non-cancerous (benign) nodules. These three stages work as follow.

A. Materials of Our proposed CAD System

LIDC database [4] has 1,018 CT scans of 7,371 nodules collected. However, only 141 patients with 156 nodules are available with diagnosis status (cancerous or not) in excel file. Additionally, 10 scans of 10 patients with diagnosis information from SPIE-AAPM database [5] were used in our CAD system.

B. Intensty-based Pulmonary Parenchyma Segmentation

Since the images include a variety of noises, median and Gaussian filters were used. The segmentation of lung nodules is an adventurous issue as inhomogeneity in the lung area, and its structure seen in CT scans; similar densities of nodules and vessels, etc. Iterative or adaptive thresholding outperforms the restrictions of ordinary threshold methods in such a problem. On the other hand, being different qualities of CT scans used in our system, global thresholding is used for some scans that are failed by iterative thresholding. Original CT scan and the result of lung lobes segmentation are shown in Figure 1(a) and Figure 1(b).

C. Nodules Segmentaion by Mathematical Morphology(MM)

To enhance the structures of the segmented images, reduce the false detection and avoid missing nodules attached to the lung walls, MM functions have been employed in the proposed system. Figure 1(c) describes the outcome of MM. Our system segmented 249 possible nodules were segmented with 162 true cases and 87 FP, 4 true nodules are lost, and recognized true 451 non-nodules correctly. In this stage, we need to segment all true lung nodules (100% sensitivity) as radiologists claimed.

D. Objects's Features Analysis and Normalization

For both CADe and CADx systems, geographical and texture or intensity based features are calculated from each nodule. Texture features are calculated by using gray level co-occurrence matrix (GLCM) which is a second order texture measure is proposed by Haralick [6]. GLCMs are calculated by taking two displacements [1,2] and four orientations [0°, 45°, 90°, 135°] into account. The features extracted are standardized by employing PCA (Principal Component Analysis).

E. False Positives Removal in CADe System

Because lung CT images contain lung vessels, tissues, etc, detection of lung nodules can misshape the structure of them which seems very similar to nodules. They are usually removed by radiologists taken a series of CT scans into account. However in our CAD system, taking one scan for one case leads to be difficult to detect lung nodules accurately. In our CAD system, the false positives (non-nodules) are detected and removed by ANFIS classifier [7]. ANFIS is intuitive using first-order Sugeno fuzzy system to interpret the numerical inputs and generate if-then rules, combining with hybrid learning algorithms; least squares in forward pass and gradient descent in backward pass of the leaning stage to reduce the error adjusting the membership parameters. In this CADe system, 209 nodules are trained and 40 cases are tested by the classifier, shown in Figure 2; the red are the results by ANFIS and the blue are the ground truth results. 17 cases out of 18 true nodules and 17 cases out of 22 non-nodules were correctly classified and 1 true nodule and 5 non-nodules were misclassified.

F. Classification of the Candidate Nodules in CADx System

For detection of lung cancer, 112 nodules are trained and 50 nodules, with 38 malignancy and 12 benignancy, are tested based on the features by ANFIS classifier. This CADx system detected 33 malignancy out of 38 and 6 benignancy out of 12.

$$Sensitivity = \frac{true\ results\ by\ CAD}{(lost + true\ results\ by\ CAD)} \quad (1)$$

$$False\ positive\ rate = \frac{lost}{(lost + tn)} \quad (2)$$

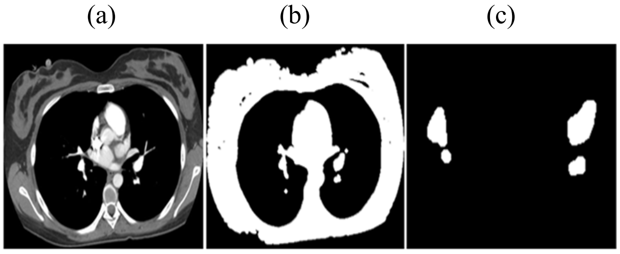

Fig. 1. *Lung nodules are isolated from lung parenchyma.*

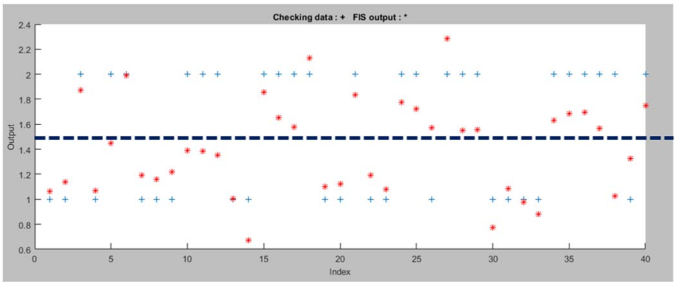

Fig. 2. *Classification result of our CADe system.*

IV. Assessing Performance and Review of Our System

To assess the performance of the system, 151 CT scans of 151 patients with diagnosis truth from the two databases [4] [5] were used. Figure 1 shows the sample results of nodules segmentation. This stage obtained 98% sensitivity and 0.16 FP per scan. In Eq.2, tn means true negatives that are correctly identified as negative results by our CAD system.

To be the autonomous CAD system, we removed non-nodules by ANFIS classifier. This CADe system obtained 94.44% sensitivity and 85% accuracy with 0.22 FP per case. After removing non-nodules from the system, the candidate nodules were classified by ANFIS classifier as cancerous or not. This diagnosis stage obtained 87% sensitivity and 78% accuracy. In this case, accuracy of the classifier is calculated by the ratio of true classified cases and total candidate objects.

V. Conclusion

LIDC-IDRI CT scans were gathered from numerous institutions. As a result, the evaluation of such database is much challenging. To get the better reliability of the system, some CT scans from SPIE-AAPM Database are applied all together. In our CAD system, performance for three stages; segmentation, CADe and CADx systems are calculated. To be robust CAD system, we should use more data from many different databases and use many efficient segmentation methods to get 100% sensitivity, and also apply more efficient classifiers for CADe and CADx systems to get 100% accuracy.

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