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An Intelligent System for Lung Cancer Diagnosis from Chest Radiographs

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Abstract: In this study we propose an Intelligent Lung Cancer Diagnosis System (ILCDS) that has been developed to detect all possible lung nodules from chest radiographs. Our system uses image processing techniques and feed forward neural networks for detection and validation of nodules. Nodules are relatively low-contrast white circular objects within the lung fields. As nodules are the most common sign of lung cancer, nodule detection in chest radiographs is a major diagnostic problem. Even experienced radiologists have trouble while distinguishing the normal pattern of blood vessels and nodules that indicate the Lung cancer. Our work is centered around two major sub systems namely Nodule Detection Subsystem (NDS) and Nodule Validation Subsystem (NVS). The Nodule Detection Subsystem is constructed using wavelet based image-processing techniques such as Besov ball projections, Laplacian of Gaussian filter and Gabor wavelet networks which are used to remove the noise from the image, find the edges of the image and detect the nodule, size and its location. The NDS detects all the possible nodules and gives the nodule-detected image. The processed image shows all nodules in the chest radiograph. Since all nodules are not cancerous, the nodules detected by the NDS are validated by the NVS. The NVS is constructed using Feed forward neural network classifiers, which classifies the nodules into non-cancerous and cancerous nodules.

Key words: ILCDS, nodule detection subsystem, nodule validation subsystem, neural networks

INTRODUCTION

Lung cancer is the primary cause of tumor deaths in most of the countries. Early detection and treatment of lung cancer is important in order to improve the five-year survival rate of cancer patients. In a healthy person, cells in the lungs divide and reproduce at a controlled rate to repair worn-out or injured tissues and let normal growth. Lung cancer develops when cells inside the lungs multiply at an uncontrollable rate. These abnormal tissue masses are called tumors. Tumors are either non-cancerous (benign) or cancerous (malignant). Medical imaging plays an important role in the early detection and treatment of cancer. It provides physicians with information essential for efficient and effective diagnosis of various diseases. Identifying the nodules from the chest radiographs can be an initial step in cancer detection. Nodules are relatively low-contrast white circular objects within the lung fields. As nodules are the most common sign of Lung cancer, nodule detection in chest radiographs is a major diagnostic problem. Even experienced radiologists have trouble while distinguishing the normal pattern of blood vessels and nodules that indicates the lung cancer. The clinical importance of chest radiographs and their complicated nature induces to develop computer aided diagnostic system to assist radiologists in reading the chest radiographs.

Automatic detection of lung nodules is the most studied problem in computer analysis of chest radiographs. Early detection of lung tumors (visible on the chest film as nodules) may increase the patient's chance of survival. But detecting nodules is a complicated task. The challenge faced by various diagnostic schemes is to distinguish true nodules from shadows, vessels and ribs. The proposed approach for nodule detection is to detect all possible initial candidate nodules with in the lung field and then detect cancerous nodules. Our work is centered around two major sub systems namely Nodule Detection Subsystem (NDS) and Nodule Validation Subsystem (NVS). The Nodule Detection Subsystem is constructed using wavelet based image-processing techniques such as Besov ball projections, Laplacian of Gaussian filter and Gabor wavelet networks which are used to remove the noise from the image, find the edges of the image and detect the nodule, size and its location. The NDS detects all the possible nodules and gives the nodule-detected image. The processed image shows all nodules in the chest radiograph. Since all nodules are not cancerous, the nodules detected by the NDS are validated by the NVS. The NVS is constructed using Feed forward neural

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network classifiers and classifies the nodules into non-cancerous and cancerous nodules.

MATERIALS AND METHODS

Computer-Aided Diagnosis (CAD) has been proven to be a very efficient approach as assistant to radiologists for improving diagnostic accuracy. Several systems were reported for detecting lung nodules on chest X-ray images in[1,2]. However, the strong distress of almost all of them is that the false positives per image are too large. How to decrease the number of false positives while maintaining a high true positive detection rate is the most important work in realizing a chest CAD system[3]. To interpret the chest radiographs, the radiologists often employ local properties like perceived intensity, uniformity, roughness, regularity, directionality, coarseness, smoothness and granulation[4]. Detection of the rib cage using Hough transformation[4], a method based on modeling correspondence[5] and a method based on the gradient gray level has been used in most of the CAD systems. Quasi-Gabor filter discussed in[7,8] has proved its high retrieval accuracy with low computational time. Wavelets provide a simple characterization for a wide variety of function smoothness spaces[9]. The norms of these spaces measure image smoothness; smaller norms imply smoother functions. Wavelets provide a simple characterization for a wide variety of function smoothness spaces. The Besov norm measures the wavelet transforms compactness, in which the optimization can be interpreted as image estimation under wavelet sparsity, which removes the noise from the image[9]. As nodules are the most common sign of lung cancer,[10] describes a system, which, following proper radiogram preprocessing, utilizes a set of decision rules and a feed forward neural network to find nodular patterns. Following a different approach,[11] proposes a two-stage system: the first one locates possible nodular patterns (thus performing a sort of attention focusing process) while the second, implemented by a convolutional neural network, discriminates nodules from non-nodules. Neural networks of the feed forward type are also in[12]. A histological classification of various benign and malignant tumors of lung as recommended by the World Health Organization is discussed in[13].

Comparing with all these works, our work discussed in this paper is different in the following ways. First, we use a Knowledge Base consisting of a large number of rules that is obtained from domain experts, as well as neural network classifiers. Second, we have built an inference engine that applies the rules using a backward chaining control flow for effective decision making. Finally we collected the images pertaining to lung cancers and stored the knowledge base using a frame system.

ARCHITECTURAL DESIGN

Our system uses image processing techniques and feed forward neural networks for detection and validation of nodules. Nodules are relatively low-contrast white circular objects within the lung fields. As nodules are the most common sign of lung cancer, nodule detection in chest radiographs is a major diagnostic problem. Even experienced radiologists have trouble while distinguishing the normal pattern of blood vessels and nodules that indicates the Lung cancer. Our work is centered around two major sub systems namely Nodule Detection Subsystem (NDS) and Nodule Validation Subsystem (NVS). The system architecture is shown in Fig. 1. The input to our system is system is chest radiographs of size 512*512. The NDS processes these radiographs. The output shows the location of all possible nodules in the lung field.

Nodule detection subsystem: The input to the NDS is JPEG chest radiograph image of size 512*512 and the output is the Processed image.

The NDS is further divided in to three sub systems

- Image Denoising Engine
- Segmentation Engine and
- Nodule Recognition Engine

Image denoising engine: The input to the Image Denoising Engine is JPEG chest radiograph image of size 512*512. The algorithm used is Multiple Wavelet Bases Denoising Using Besov Ball Projections and the output is the denoised image of size 512*512.

Removing noise from images is an important problem in image acquisition and processing. Spatial filters have been used as the traditional means of removing noise from images. The filters usually smooth the data to reduce the noise, but this process also blur the data. Among many approaches denoising by wavelet co-efficient thresholding and its variants provide excellent performance for removing noise. Simple and fast wavelet thresholding suppresses the corrupting noise and preserve the edges.

Segmentation engine: The input to the segmentation engine is the output of the Image Denoising Engine. The algorithm used is Laplacian of Gaussian Filter and the output is the edge-detected image of size 512*512. The major advantage of using Laplacian of Gaussian Filter is

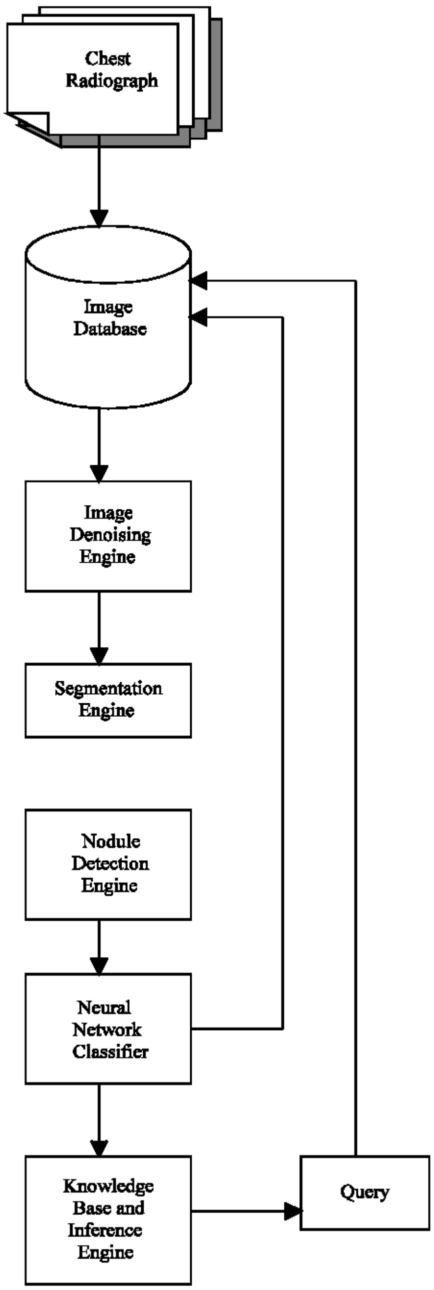

Fig. 1: System architecture

that no prior explicit knowledge about the actual shape of the nodules and the structure of image background is needed.

Nodule recognition engine: The input to the nodule recognition engine is the edge-detected image of size 512*512, which is the output of the segmentation engine. The algorithm used is Gabor Wavelet Networks and the output is the nodule-detected image of size 512*512. The Gabor Wavelet Network is constructed using Gabor Wavelet Transforms.

Nodule validation subsystem: The input to the NVS is the processed image of size 512*512, which is the output of the nodule recognition engine. Back Propagation network has been used to classify the nodules identified as cancerous or non-cancerous. Initially the neural network was trained to classify nodules. Expert radiologists were involved during this phase. Based on the classification a numeric identifier was assigned for each radiograph image, the severity level and the treatment recommended was also recorded. The numeric identifier represents the severity level and is not unique. The above data is stored in the knowledge base. Given an input query image, the image undergoes all preprocessing stages as shown in Fig. 1 and the neural network classifier generates the numeric identifier, which is an input to the knowledgebase. The knowledgebase in turn provides the radiologist with the severity level and the treatment recommended. This aids the radiologist in decision-making.

RESULTS

We have implemented our work using MATLAB, Oracle 8i and JDK 1.3. We have used four hundred images for the purpose of training. We carried out the testing with another fifty images. The neural network classifier was able to classify thirty eight images correctly as true positive. Four images were classified as true negative and eight images were classified as false positive.

CONCLUSION

Results highlight that detection sensitivity is largely dependent on nodule subtlety, as defined by expert radiologists that account for size, contrast and anatomical position of lesions. The use of a data set with a larger number of subtler lesions is highly desirable. A Neuro Fuzzy approach can be used through which vagueness in the data set can be handled.

REFERENCES

1. Lin, J., S.B. Lo, A. Hasegawa, M.T. Freedman and S.K. Mun, 1996. Reduction of false positives in lung nodule detection using a two-level neural classification, IEEE Trans. On Medical Imaging, 15: 206-217.

2. Xin-Wei, Xu, K. Doi, T. Kobayashi, H. MacMahon and M.L. Giger, 1997. Development of an improved CAD scheme for automated detection of lung nodules in digital chest Images, Medical Physics, 24: 1395-1403.
3. Yoshida, H. and K. Doi, 2000. Computerized detection of pulmonary nodules in chest radiographs: Reduction of False Positives Based on Symmetry Between Left and Right Lungs. Proceedings of SPIE in Medical Imaging, pp: 97-102.
4. Tetsuo S., Y. Yoshio and S. Naozo, 1995. Construction of Structural Edge Map on Chest Radiograph Using Hough Transformation and Line connection, Systems and Computers, 26: 71-78.
5. Takeshi, H., F. Hiroshi and X. Jing, 1997. Development of automated detection system for lung nodules in chest radiograms, IEEE Transactions on Medical Imaging, pp: 71-74.
6. Matthew B., W. Laurence, D. Bruce, G. Robert and C. Sun, 1998. Knowledge-based method for segmentation and analysis of lung boundaries in chest X-ray images, Computerized Medical Imaging and Graphics, 22: 463-477.
7. Park, M., J. Jin and L. Wilson, 2002. Fast Content-Based Image Retrieval Using quasi-Gabor Filter and Reduction of Image Feature, 5th IEEE Southwest Symposium on Image Analysis and Interpretation, pp: 178-182.
8. Park, M., J. Jin and L. Wilson, 2002. Hierarchical indexing images using weighted low dimensional texture feature, Fifteenth IAPR International Conference on Vision Interface, pp: 39-44.
9. Hyeokho Choi, Member, IEEE and G. Richard, Baraniuk, Fellow, IEEE, 2004. Multiple Wavelet Basis Image Denoising Using Besov Ball Projections. IEEE Signal Processing Letters, 11: 717-720.
10. Xu, X.W., K. Doi, T. Kobayashi, H. MacMahon and M. Giger, 1997. Development of an improved CAD scheme for automated detection of lung nodules in digital chest images, Medical Physics, 24: 1395-1403.
11. Lo, S.C.B., S.L.A. Lou, J.S. Lin, M. Freedman, M.V. Chien and S.K. Mun, 1995. Artificial convolutional neural network techniques and applications for lung nodule detection, IEEE Transactions on Medical Imaging, 14: 711-718.
12. Penedo, M., M. Carreira, A. Mosquera and D. Cabello, 1998. Computer-aided diagnosis: A neural-network based approach to lung nodule detection, IEEE Transactions on Medical Imaging, 17: 872-880.
13. Online Cancer Help- www.cancerhelp.org.uk
14. Am. Cancer Soc. Cancer Facts and Figures 2001. www.cancer.org
15. USU Department of Radiology and Radiological Sciences. http://rad.usu.