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IMPROVING THE CONSPICUITY OF LUNG NODULES BY USE OF "VIRTUAL DUAL-ENERGY" RADIOGRAPHY

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Abstract— **In the field of medical image processing, computer programs have been developed and approved for use in clinical practice that aid radiologists in detecting the abnormalities on radiology exams. In this study, a Computer-aided detection (CADe) scheme with improved sensitivity and specificity is developed. Chest radiograph(CXR) images are used as the input, which is then segmented using Multi segment active shape model (M-ASM). Massive Training Artificial Neural Network(MTANN) is used to suppress the ribs and clavicles as a result of which, Virtual Dual-Energy(VDE) image is developed. In addition, an Hop-Field Neural Network(HNN) is used to improve the rib contrast. Features are extracted from the original image and the VDE image. A nonlinear support vector machine(SVM)classifier was employed for classification of the nodule candidates and a linear discrimination analysis is used to detect the nodules.**

Keywords—Chest radiography(CXR); computer-aided detection (CAD); rib suppression; virtual dual energy(VDE).

I. INTRODUCTION

CANCERis one of the most serious health problem in the world. The mortality rate of lung cancer is the highest among all other types of cancer. Survival from lung cancer is directly related to its growth at its detection time. The overall five year survival rate for lung cancer patients is only 14%.Early detection and treatment of lung cancer can improve the survival rate by 50% if it is detected at an early stage. The earlier the detection is, the higher the chances of successful treatment are. In recent years, image processing mechanisms are widely used in several medical areas for improving early detection of diseases. For detection of lung cancer, various radiography techniques such as CXR,CT,MRI and PET are used. However, chest radiographs(CXRs) are used in our paper because it is the most cost-effective technique when compared to other radiography techniques. But the main drawback of CXRs is that the radiologists cannot detect the nodules accurately.82-95% of the nodules will be missed because of the overlapping ribs and clavicles. Hence such nodules must be detected by suppressing the ribs and clavicles.

Computer-aided detection(CADe) scheme was developed to identify the suspicious features on the image and brings them to the attention of radiologists in order to decrease the false-negative readings. Initially dual-energy subtraction technique was used to reduce the overlapping ribs and clavicles. It is a technique used for separating the soft tissue from bones in CXRs by using two x-ray exposures at two different energy levels. But this technique is used only in a limited number of hospitals because specialized equipment is required and the radiation dose can be double. To overcome these drawbacks, an image processing technique called virtual dual-energy (VDE) radiography for suppressing ribs and clavicles in CXRs is used.

II. RELATED WORKS

Elizabeth et al. [2] in their work have presented a computer-aided diagnosis system capable of selecting a significant slice for the analysis of each nodule from a set of slices of a computed tomography (CT) scan in digital imaging and communications in medicine (DICOM) format has been developed for the diagnosis of lung cancer. Here RBFNN(Radial Basis Function Neural Network) is used. An accuracy of 94.44% has been achieved in classifying the nodules as cancerous and non-cancerous. Reduces the computational complexity of the CAD system. The severity and rate of growth of lung cancer is not identified.

Azian azamimi et al. [7] in their work have proposed a detection system using cellular neural network (CNN) is developed in order to help the doctors to recognize the doubtful

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lung cancer regions in x-ray films. In this study, a CNN algorithm for detecting the boundary and area of lung cancer in x-ray image has been proposed. Computer simulation result shows that our CNN algorithm is verified to detect some key lung cancer symptoms successfully and has been proved by radiologist. Low-cost and computerized detectionmethod for lung cancer.The type and stage of lung cancer are still cannot be known.

Manikandan et al. [8] in their work have presented Support vector machine (SVM) is the state-of-the-art classifier used in real world pattern recognition applications. One of the design objectives of SVMclassifiers using non-linear kernels is reducing the number of support vectors without compromising the classification accuracy. To meet this objective, decision-tree approach and pruning techniques are proposed in the literature. In this study, optimum threshold (OT)-based pruning technique is applied to different decision-tree-based SVM classifiers and their performances are compared. The application of OT technique reduces the minimum-time required for recognition. Classification problems are not done.

Ashwin et al. [9] have mentioned that a two stage CAD system in which the first stage involves pre-processing applied for a better quality image to enable higher success rate on detection following which the cancerous nodule region is segmented. The second stage involves artificial neural network (ANN) architecture which is trained using a modified BFGS algorithm. It provides accuracy of 96.7% and also better specificity. Contrast Limited Adaptive Histogram Equalization technique is used to improve the image quality by proficient image contrast enhancement factor.

III. SYSTEM ARCHITECTURE

The proposed system architecture is divided in to two phases. During the first phase, the CXR and its corresponding dual energy images are taken from JSRT database. The lung regions are then segmented and the ribs and clavicles surrounding the CXR are suppressed to get a VDE image. An improved VDE image would be formed by improving the rib contrast.

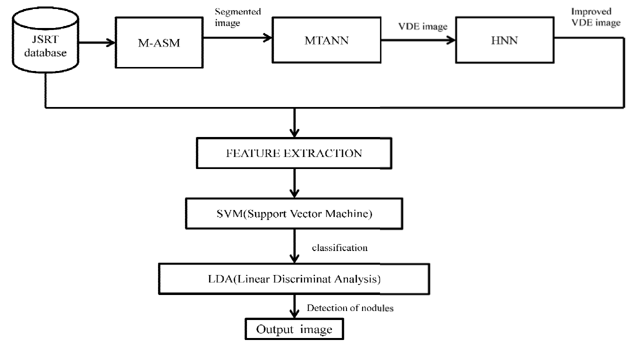

Fig.1. System Architecture

During the second phase, features for both the original CXR image and the improved VDE image will be extracted. The candidates will be classified using a classifier and the nodules will be detected. Once the nodules are detected, the output image is produced.

Images are obtained from JSRT database which is publicly available. When a query chest X-ray image is given to the CAD system, it is segmented to extract the lung region. After the lung is segmented , the bones surrounding the region will be suppressed by using Massive Training Artificial Neural Network. The rib contrast is improved by using Hop-field Neural Network. Features extracted from the original image and the improved VDE image is used for classification.

A. M-ASM

Lung segmentation is a critical component of a CADe scheme. It can prevent the occurrence of FPs outside the lung fields. Many methods have been proposed for segmenting the lungs in CXRs,such as 1. rule-based segmentation methods, 2. pixel-based methods, 3.hybrid methods, and 4.deformable model-based methods. Because the prior information can easily be incorporated into the segmentation procedure, an active shape model ASM has been used for lung segmentation in CXR.Because a conventional ASMcannot cover changes and variations in the entire boundariesof the lungs accurately,we developed a multi segment ASM ,M-ASM that is adaptive to each of multiple segments ofthe lung boundaries which we call a multisegment adaptationapproachas illustrated in Fig.2. Because the nodes inthe conventional ASM are equally spaced along the entirelung shape, they do not fit lung shape parts with high curvatures.

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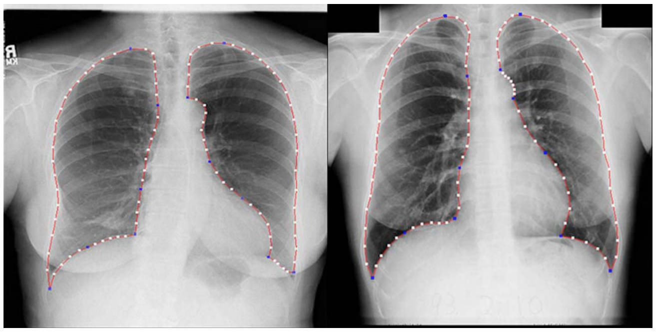

FIG. 2. Lung segmentation by using an M-ASM. Each blue point represents the transitional landmarks between two boundary types e.g., the heart and the diaphragm, the aorta, and the apex of the left lung.

In our method, the model was improved by fixating of the selected nodes at specific structural boundaries which we call transitional landmarks. Transitional landmarks identified the change from one boundary type e.g., a boundary between the lung field and the heart to another e.g., a boundary between the lung field and the diaphragm. This resulted in multiple segmented lung-field boundaries where each segment is correlated with a specific boundary type heart, aorta,rib cage, diaphragm, etc.. The node-specific ASM was built by using a fixed set of equally spaced nodes for each boundary segment. Our lung M-ASM consisted of a total of 50 nodes for each lung boundary. The nodes were not equally spaced along the entire contour. A fixed number of nodes were assigned to each boundary segment, and they were equally spaced along each boundary as shown in Fig.2.

This allowed the local features of nodes to fit a specific boundary segment rather than the whole lung, which resulted in a marked improvement in the accuracy of boundary segmentation. From the training images, the relative spatial relationships among the nodes in each boundary segment were learned in order to form the shape model. The nodes were arranged into a vector *x* and projected into the principal component shape space by means of the following expression:

$$b = v^T(x - \bar{x}) \qquad (1)$$

where $V=V_1V_2...V_M$ is the matrix of the first M eigen vectors for the shape covariance matrix and $b=b_1b_2...b_{M.}\ ^T$ is a vector of shape coefficients for the primary axes. The shape coefficients generate only a plausible shape and projected back to node coordinates with the following expression:

$$x = \bar{x} + vb \qquad (2)$$

Here, m usually has value between 2 and 3.

B. MTANN

When lung nodules overlap with ribs or clavicles in chest radiographs, it can be difficult for radiologists as well as computer-aided diagnostic (CAD) schemes to detect these nodules. In this study, we developed an image-processing technique for suppressing the contrast of ribs and clavicles in chest radiographs by means of a multi-resolution massive-training artificial neural network (MTANN). An MTANN is a nonlinear filter that can be trained by use of input chest radiographs and the corresponding “teaching images. We employed “bone images obtained with a dual-energy subtraction radiography system as the teaching images. For effective suppression of ribs having various spatial frequencies, we developed a MTANN consisting of multi-resolution decomposition/composition techniques and three MTANNs for three different-resolution images. After training with input chest radiographs and the corresponding dual-energy bone images, the multi-resolution MTANN was able to provide "bone-image-like" images which were similar to the teaching dual-energy bone images. By subtracting the bone-image-like images from the corresponding chest radiographs, we were able to produce "soft-tissue-image-like" images where ribs and clavicles were substantially suppressed. The major advantages of our virtual dual-energy radiography compared to "gold standard" duel-energy subtraction radiography are: (1) no additional radiation dose to patients is required, and (2) no specialized equipment for generating dual-energy x-rays is required. Our image-processing technique for rib suppression by means of a multi-resolution MTANN would be useful for radiologists as well as for CAD schemes in the detection of lung nodules on chest radiographs.

C. Hop-field neural network

In our project work, an feed back neural network called Hop-field Neural Network is used. Since MTANN is a feed forward neural network and it uses only fixed parameter to adjust the rib contrast. Hence Hop-field neural network is used for solving the optimization problem. Hop-field Neural Network(HNN) can have signals travelling in both directions by introducing loops, propagating values from the hidden and output layers backward to earlier layer.

Their state changes continuously until they reach an point. It solves the image change detection problem between two images. The network topology is built so that each pixel in the different image is a node in the network. Each node is characterized by its state which determines if a pixel has changed. The HNN model allows each node to take on continuous state values.

The units in the hop field are binary threshold units. The units only take on two different values for their states and the value is determined by whether or not the units input excess their threshold. Hop-field network have units that take values 1 or -1.

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D. Feature Extraction

Feature extraction is one of the most important step in CAD system. It helps to CAD system to take correct decision and increase its accuracy by providing distinguished features. The main aim is to extract maximum distinguished features. Feature extraction properties are fed as an input to the CAD system. Feature extraction provides certain parameters on the basis of which computer system takes decision. The entire feature which are calculated from the image convey some information regarding lung nodule.

Sixty morphologic and gray-level-based features were extracted from each candidate from both original and VDE CXRs which were smaller than the number of nodules in the training database. Some nodules had similar characteristics to those of bones in terms of the shape, the size, the contrast, and the orientation. The features of these nodules may be suppressed in VDE image. Detected nodules in the nodule candidate detection step may be misclassified as non-nodules based on the features in the original image or VDE image alone. To improve the classification performance, we also extracted the same feature set at the corresponding locations of the detected nodule candidates in the corresponding original image. Nodule candidate segmentation was repeated both in original and VDE images. Because of the bone suppression, the segmented contour of nodule candidate overlapped with ribs and clavicles may be more precise than that from original CXR and the feature based on the segmentation results may be more effective.

E. Classification of candidates

A nonlinear SVM was employed for classification of the nodule candidates into nodules or non-nodules. In our CADe scheme, only CXR acquired with a standard radiography system was inputted into our system and no specialized equipment for generating VDE image, but only software, is required. The SVM classifier was trained/tested with a leave-one out cross-validation test. Features for the LDA were selected by using the stepwise feature selection method. With the selection method, we determined a single set of features from *M* runs of a leave-one-out cross-validation test *M* is the number of features. Each feature was selected at each run after we accumulated all *N* results from the run *N* is the number of samples.

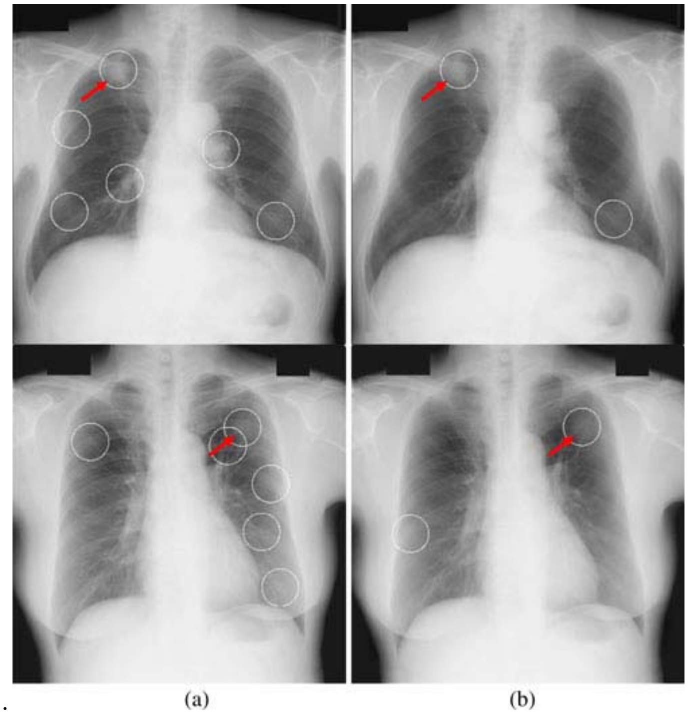

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Fig 3. Illustration of the improvement in specificity by our VDE technology. CADe marks are indicated by circles

IV. PERFORMANCE EVALUATION

The overall performance of our VDE-based CADe scheme combines the VDE image with original image and the original CADe scheme for the JSRT database. The performance of the VDE-based CADe scheme was substantially higher than that of the original CADe scheme. It is difficult to comparisons with previously published CADe schemes because of different databases available. It also includes different TP criteria, different evaluation procedures, optimization parameters and operating points. Table I indicates the performance comparisons among different CADe schemes. Hardie et al stated that their scheme has set 80% of nodules in the JSRT database with 5 FPs per image.

TABLE I
PERFORMANCE COMPARISON OF CADe SCHEMES THAT USES JSRT DATABASE

	Sensitivity	FPs	Database
Hardie et al	80%	5.0	Nodule cases in JSRT
Chen et al	79%	5.0	Nodule cases and all normal cases in JSRT.

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VDE-based CADe	85%	5.0	Nodule cases and all normal cases in JSRT.

The performance of our VDE-based CADe scheme was substantially higher than that of Hardie's CADe scheme. VDE-based CADe scheme has achieved a sensitivity of 85.0% where as Hardie's CADe scheme achieved a sensitivity of 80.0%

V. DISCUSSION

Chest radiography is a powerful tool for diagnosing many diseases, but it is difficult to find the spot on the lungs.80-90% of the nodules will be missed upon initial reading of chest radiography. The main disadvantage is poor conspicuity and it is hard to find against the background of overlying anatomy. One method to reduce the overlying anatomy is dual-energy imaging.

It takes two radiographs at two different mean beam energies. These radiographs are then combined to form a subtraction image that highlights a soft tissue image. The soft tissue image shows better visualization of the nodules because the ribs are made to vanish. The advantages of VDE over dual energy subtraction technique is that no additional dose to patient is required and no specialised equipment for generating dual energy x-rays is required.

We used the publicly available JSRT database to evaluate our CADe scheme. The observer studies indicated that radiologists found it particularly difficult to detect the very and extremely nodules in the JSRT database and the radiologist detected only 44% of the hard cases. With an average 4 FPs per image, our VDE-based scheme correctly marked 66.7% of the hardcases. There was 10% improvement than our original scheme, and it also had a higher performance than that proposed by Schilham *et al*., which is 41% [13]. This was a very encouraging result that our method could provide a useful clinical tool. The improved CADe scheme incorporating VDE image had a special characteristic for detecting the hard subtle nodules.

VI. CONCLUSION

In this paper, we have developed a CADe scheme for improving the clear visibility of lung nodules using virtual dual-energy radiography in which the ribs and clavicles are suppressed. The performance of the CADe scheme is improved substantially.The performance of the CADe scheme provided a substantial improvement against the original CADe scheme. The rib contrast parameter is increased substantially which in turn increases the performance.

REFERENCES

[1] Sheng Chen and Kenji Suzuki, "Computerized Detection of Lung Nodules By Means of Virtual Dual-Energy Radiography, *"IEEETransactions on Biomedical Engineering,* vol.60, no. 2, Feb. 2013.

[2] D.S.Elizabeth, H.K.Nehemiah, "Computer-aided diagnosis of lung cancer based on analysis of the significant slice of chest tomography image, *IET* Dec. 2011.

[3] F. Li, R. Engelmann, K. Doi, and H. MacMahon, "Improved detection of small lung cancers with dual-energy subtraction chest radiography," AJRAmer. J. Roentgenol., vol. 190, pp. 886–891, Apr. 2008.

[4] B. van Ginneken, B. M. ter Haar Romeny, and M. A. Viergever,"Computer-aided diagnosis in chest radiography: A survey," *IEEETrans.Med. Imag*., vol. 20, no. 12, pp. 1228–1241, Dec. 2001.

[5] K. Suzuki, J. Shiraishi,H.Abe,H.MacMahon, andK.Doi, "False-positive reduction in computer-aided diagnostic scheme for detecting nodules inchest radiographs by means of massive training artificial neural network,"*Acad. Radiol*., vol. 12, pp. 191–201, Feb. 2005.

[6] K. Suzuki, H. Abe, H. MacMahon, and K. Doi, "Image-processing for suppressing ribs in chest radiographs by the means of massivetraining artificial neural network (MTANN)," *IEEE Trans. Med. Imag,* vol. 25, no. 4, pp. 406–416, Apr. 2006.

[7] Azian Azamimi Abdullah ,Hasdiana Mohamaddiah, "Development of Cellular Neural Network Algorithm for Detecting Lung Cancer Symptoms", *IEEE EMBS Conference*,2010.

[8] J.Manikandan, B.Venkataramani "Evaluation of multiclass support vector machine classifiers using optimum threshold-based pruning technique*", IET,* Nov 3,2010.

[9] S. Ashwin, S. Aravind kumar, " Efficient and Reliable Lung Nodule Detection using a Neural Network Based Computer Aided Diagnosis System", *IEEE Trans*, 2012.

[10] M.Egmont-petersen, D. de Ridder, " Image processing with neural networks-a review",*Elsevier*,2002.

[11] K. Suzuki,H.Abe, F. Li, andK.Doi, "Suppression of the contrast of ribs inchest radiographs by means of massive training artificial neural network,"in *Proc. SPIE Med. Imag*., San Diego, CA, 2004, pp. 1109–1119.

[12] S. Chen, K. Suzuki, and H. MacMahon, "Development and evaluation of a computer-aided diagnostic scheme for lung nodule detection in chest radiographs by means of two-stage nodule enhancement with support vector classification," *Med. Phys.*, vol. 38, pp. 1844–1858, 2011.

[13] J. Shiraishi, S. Katsuragawa, J. Ikezoe, T. Matsumoto, T. Kobayashi, K. Komatsu, M. Matsui, H. Fujita, Y. Kodera, and K. Doi, "Developmentof a digital image database for chest radiographs with and withouta lung nodule: Receiver operating characteristic analysis of radiologists'detection of pulmonary nodules," *AJR Amer. J. Roentgenol.*, vol. 174, pp. 71–74, Jan. 2000.

[14] J. Shiraishi,Q. Li, K. Suzuki,R. Engelmann, andK.Doi, "Computer-aided diagnostic scheme for the detection of lung nodules on chest radiographs:Localized search method based on anatomical classification," *Med. Phys.*, vol. 33, pp. 2642–2653, Jul. 2006.

[15] R. C. Hardie, S. K. Rogers, T.Wilson, and A. Rogers, "Performance analysisof a newcomputer aided detection system for identifying lung noduleson chest radiographs," *Med. Image Anal.*, vol. 12, pp. 240–258, Jun. 2008.

[16] T. F. Cootes, A. Hill, C. J. Taylor, and J. Haslam, "Use of active shape models for locating structures in medical images," *Image Vis. Comput.*, vol. 12, pp. 355–365, 1994.

[17] Serra, Image Analysis and Mathematical Morphology, vol. 1. New York: Academic, 1982.

[18] L. Vincent and P. Soille, "Watersheds in digital spaces: An efficient algorithm based on immersion simulations," *IEEE Trans. Pattern Anal. Mach.Intell.*, vol. 13, no. 6, pp. 583–598, Jun. 1991.

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[19] J. P. Egan, G. Z. Greenberg, and A. I. Schulman, “Operating characteristics, signal detectability, and the method of free response,” *J. Acoust. Soc. Amer.*, vol. 33, pp. 993–1007, 1961.
[20] K. Suzuki, H. Abe, F. Li, and K. Doi, “Suppression of the contrast of ribs in chest radiographs by means of massive training artificial neural network,” in *Proc. SPIE Med. Imag.*, 2004, vol. 5370, pp. 1109–1119.
[21] K. Suzuki, I. Horiba, and N. Sugie, “Neural edge enhancer for supervised edge enhancement from noisy images,” *IEEE Trans. Pattern Anal. Mach.Intell.*, vol. 25, no. 12, pp. 1582–1596, Dec. 2003.
[22] K.K.Thyagaharajan , G.Nagarajan , “Semantically Effective Visual Concept Illustration for Images” 5th International Conference on Information and Multimedia Technology , International Journal of Future Computer and Communication, Vol.3,No.2,Pg:124-128,April 2014.
[23] K.Madhu, R.I.Minu (2013) “Image Segmentation using Improved JSEG” IEEE International Conference on Pattern Recognition, Informatics and Mobile Engineering , Periyar university

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