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Detection & Classification of Lung Nodules Using multi resolution MTANN in Chest Radiography Images

Sridhar.R[1], Saravanakumar.S[2]

[1] PG Student, Applied Electronics, Dept of ECE, Anna University Regional Centre Coimbatore, Tamilnadu, India.

[2]Asst. Professor, Dept of ECE, Anna University Regional Centre Coimbatore, Tamilnadu, India.

ABSTRACT

The main aim is to develop a computerized detection of lung nodules in chest radiography image (CXR).Most of lung nodules that are missed by radiologists as well as computer-aided detection (CADe) schemes overlap with ribs or clavicles in (CXRs). Computed tomography is used to detect the lung nodules but it's costlier. The proposed method uses the X-Rays, are preferred due to cost effective, low radiation dose and effective diagnostic tool. Computerized Detection Scheme system detected nodule candidates on VDE images by use of lung segmentation and morphological filtering techniques. Segmentation of lung regions based on our M-ASM and nodules at the lung borders by using coarse to fine segmentation techniques and watershed segmentation algorithm. The classification and feature analysis of the nodule candidates into nodules or non nodules by use of non linear Support Vector Machine (SVM) with Gaussian kernel classifier. By implementing this work, experimental results show that the different rib contrast parameter, smoothness and entropy are compared with conventional method.

KEYWORDS- *CXR, MTANN, VDE, Feature extraction.*

I. INTRODUCTION

In this modern world, the total number of deaths caused by cancer is rising day by day. Lung cancer is currently the second most common cancer in both men and women and is the top cause of all cancer deaths. There is a direct link of tobacco smoking and other impurity and dirty exposures to lung cancer making it the leading preventable cause of death. Every year, more than eight million people worldwide die from chest diseases. For detection of lung cancer, various radiography techniques such as CXR, CT, MRI and PET are used. Chest radiography (chest X-ray: CXR) is by far the most commonly used diagnostic imaging technique for identifying chest diseases such as lung cancer, tuberculosis, pneumonia, and pulmonary emphysema. CXRs are regularly used for detecting lung cancer as there is support that early detection of the disease can result in a more hopeful diagnosis. However, chest radiographs (CXRs) are used in our paper because it is the most cost-effective technique when compared to other radiography techniques. Because CXRs are so widely used, growth in the detection of lung nodules in CXRs could have a significant impact on early detection of lung cancer.

Generally the detection of lung nodule system consists of three major steps involved. First, lung segmentation is preprocessing step for enhancement. Then, Segmentation of lung fields based on our multi-segment active shape model (M-ASM) and a background-trend correction was applied to the segmented lung field .Second, Two-stage nodule enhancement and nodule candidate detection. Segmentation of nodule candidates by use of our clustering watershed algorithm; and Third, Feature analysis and classification of the nodule candidates into nodules or non-nodules by use of a nonlinear support vector machine (SVM) classifier.

II. MATERIALS AND METHODS

In first step, hardcopy of images are converted into the soft copy of images with the help of high resolution scanner. These scanned images are stored in the storage drive location for additional analysis and processing it. These Scanned images are imported into the computerized detection scheme system. Computerized detection scheme system performs two main tasks namely detection and classification. Detection is further classified as image acquisition, enhancement and segmentation. In image acquisition all the scanned images are resized into the standard size. As the Computerized detection scheme system algorithm are developed for specific size image.

Enhancement process of scanned image is required before applying any segmentation and feature extraction algorithm. During the scanning process and storing process of X-ray image, a lot of unrelated information (noise) is added. For removing unrelated information and for enhancing the X-ray image, Total variation De-noise, Wiener filter, Gaussian smoothing pre processing techniques is employed. The figure 2 shows the pre processing techniques of X- ray image.

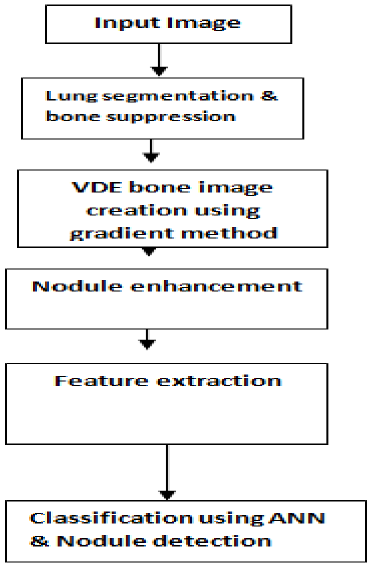


Fig. 1 shows a computerized detection scheme system.

A. Multi resolution MTANN SCHEME FOR THE LUNG NODULE DETECTION

To address the issue of the availability of dual-energy systems developed an image-processing technique called virtual dual energy (VDE) radiography for suppressing ribs and clavicles in CXRs by means of multi resolution MTANN. The dual-energy images were used as the bone (trained) images for training of the multi resolution MTANN. The trained MTANN suppressed ribs and clavicles in standard CXRs considerably, while the visibility of nodules and lung vessels was maintained.

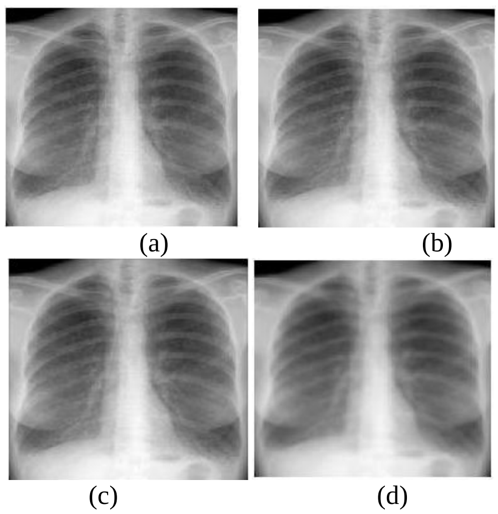


Fig. 2 shows pre processing step for X-ray image
(a) Input image (b) wiener filter (c) Gaussian smoothing (d) TV de-noise.

B. SEGMENTATION OF LUNGS

To improve the performance of the computerized detection schemes in Medical field, there are many algorithms are used. To provide a reliable and accurate detection of nodules in the CXR images, the segmentation of lungs is the mostly used pre processing step in different types of computerized detection schemes. The Lung Segmentation is very important to find out the lung nodules which present in margin and edge portions of the lung. The tiny nodules in the lung are missed by seeing through naked eyes. Thus, the proposed algorithm is used to improve the performance and parameters are contrast, smoothness, entropy of the lung nodule image.

Lung segmentation is a critical component of a computerized detection scheme system. It can prevent the occurrence of FPs outside the lung fields. A lot of methods have been proposed for segmenting the lungs in CXRs such as 1. Rule-based segmentation methods, 2. Hybrid methods, 3. Pixel-based methods, and 4.deformable model-based methods. Because the earlier information can easily be included into the segmentation procedure, an active shape model (ASM) has been used for lung segmentation in CXR. Because a conventional ASM cannot cover changes and variations in the entire boundaries of the lungs accurately, we developed a multi segment ASM (M-ASM) that is adaptive to each of multiple segments of the lung boundaries (which we call a multi segment adaptation approach). In our method, the model was improved by fixating of the selected nodes at specific structural boundaries which we call transitional landmarks .This resulted in multiple segmented lung-field boundaries where each segment is correlated with a specific boundary type heart, rib cage, diaphragm, etc,. The node-specific ASM was built by using a fixed set of equally spaced nodes for each boundary segment.

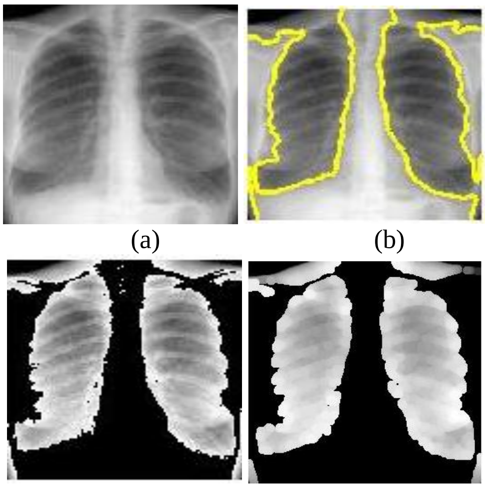


Fig. 3 shows segmentation of lungs based on our M-ASM (a) input image (b) M-ASM (c)M-ASM segmented lung image (d)BTC image.

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 are arranged into a vector x and projected into the principal component shape space by means of the following expression:

$$b = V^T (x-x')$$

Where $V= (V1V2\ldots VM)$ is the matrix of the first M eigenvectors for the shape covariance matrix and $b= (b1b2\ldots bm)^T$ is a vector of shape coefficients for the primary axes. The shape coefficients are constrained to lie in a range $\pm m\sqrt{\lambda i}$ to generate only a plausible shape and projected back to node coordinates with the following expression:

$$x=x'+Vb$$

Here, m usually has value between 2 and 3, and it was 2.5 in our experiment. The segmentation accuracy was computed by using the overlap measure Ω,

$$\Omega = \frac{TPseg}{TPseg + FPseg + FNseg}$$

Where TPseg was the area correctly classified as a lung field, FPseg was the area incorrectly classified as a lung field, and FNseg was the area incorrectly classified as the background. After the lungs were segmented, using a background-trend correction technique was applied to the segmented lung fields. Then, a second-order (bivariate) polynomial function was fitted to each of the left and right lung fields individually, as illustrated in Fig.3, represented by

$$F(x, y) = ax^2 + by^2 + c\,x\,y + d\,x + e\,y + f$$

where *a*, *b*, *c*, *d*, *e*, and *f* are coefficients are calculated for each case in the image.

C. CREATION OF VDE BONE IMAGES

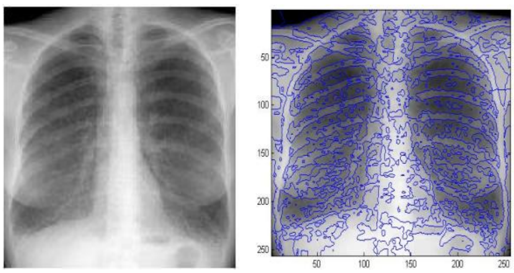
Chest radiography is one of the most commonly performed diagnostic imaging examinations. The Virtual Dual-Energy imaging develops the different physical properties of soft-tissue and bony structures that affect the attenuation of x-ray photons at different x-ray energies. In this technique commonly used to capture a low-energy image and a high-energy image during a single examination. This results can making a pair of energy subtraction images, permitting either bone or soft tissue to be masked for interpretation. This technique utilizing a massive training artificial neural network (MTANN) can perform both enhancement of a particular opacity and suppression of other opacities in medical images.

With virtual dual-energy radiography (VDE), rib and soft-tissue components of chest radiography images can be separated by software (without specialized equipment), and soft-tissue and bone images can be formed .The (lung) nodules in chest x-rays are often partially obscured by overlying bone such as the ribs or clavicle. The main advantages of simulated virtual dual-energy radiography compared to conventional dual energy are:

1. There is no additional radiation dose to patients is required.
2. There is no specialized equipment for creating of the VDE images.

The multi-resolution MTANN is a supervised non-linear filter consisting of a linear output artificial neural network model capable of operating on image data directly. The developer can uses MTANN tool has two stages, a training stage and an application stage.

In the training stage, the MTANN is trained with input from chest x-rays and corresponding teaching bone images obtained with a dual-energy radiography system. In the application stage, the trained MTANN is applied to a standard chest x-ray to provide a bone-image-like image where the ribs are extracted. The bone-image-like images can then be subtracted from the original image to obtain a soft-tissue-like image where the ribs are suppressed.



(a) (b)

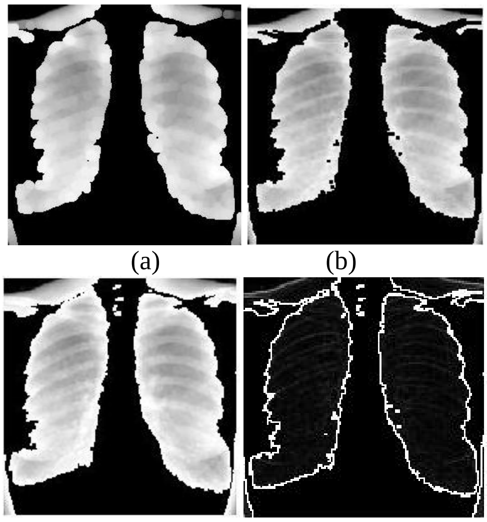
Fig.4 shows the creation of VDE bone images (a) input image (b) VDE image.

With the VDE tool, bones can be suppressed, and the false positive segment can be decreased. Utilizing the VDE application, it was able to suppress the ribs and allow for better temporal subtraction image comparison than with conventional chest x-rays.

In our computerized scheme, we applied the VDE technology to reduce the rib induced segment and to find out the nodules which are overlapping with the ribs and clavicles in the lungs. This VDE technology performs by two stages Enhancement techniques, watershed based segmentation and by grey level morphology.

D. NODULE ENHANCEMENT

We developed a method, two-stage nodule-enhancement techniques and applied it to the preprocessed image to obtain a nodule enhanced image and a nodule likelihood map. Then, our proposed method two-stage nodule enhancement techniques are produced a nodule-enhanced image and a nodule- likelihood map. The first stage of this technique enhanced nodules by use of two different types of gray-level morphologic opening operators, one enhanced nodules and the other one suppressed ribs. The second stage of nodule enhancement technique is converted the nodule-enhanced image into a nodule-likelihood map by use of a directional gradient magnitude filter. First, a gray-level morphologic opening operator with a nodule template was applied to the preprocessed image to obtain a nodule enhanced image, as illustrated in Figure 5.



(a) (b)

(c) (d)

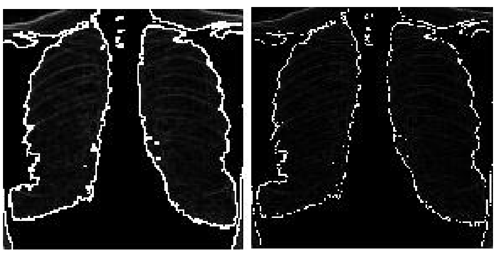
Fig. 5 shows the nodule enhancement by using the gray-level morphologic filter. (a) morphological opening (b) Erosion (c)Dilation (d) nodule-enhanced image.

(i) Morphological Operations

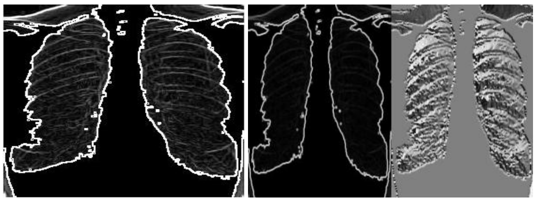
In the first step, grey level morphological operation was induced for the detection of the nodules overlapping ribs and clavicles. Morphology is a set of image processing operations that process images based on its shapes. Morphological operations apply a structuring element to a corresponding input image, creating an output image of the same size. The basic morphological operations are dilation and erosion.

Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object borders in an image. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image. The figure 5 shows the morphological operations of corresponding input image. We applied a binary morphologic erosion operator to the nodule candidate regions to break connections between the nodule and non-nodule regions. After that, a binary morphologic dilation operator dilated the connected region and representing a rough nodule candidate was obtained.

Next, some gray-level morphologic opening operators with rib templates were applied to the preprocessed image to produce a rib-like-pattern enhanced image. Finally, the rib enhanced image was subtracted from the nodule-like-pattern-enhanced image to produce a nodule enhanced image. In the image, the nodule-like image patterns have larger pixel values; the rib-like image patterns and other patterns have smaller pixel values. The morphological filter can enhance a nodule effectively.



(a) (b)



(c) (d)

Fig.6 shows the nodule likelihood map pattern obtained by using our second-step nodule enhancement. (a)Nodule-likelihood map image. (b) rib-like pattern (rib suppression image) (c) gradient image.(d) Gradient magnitude, Gmag (left), Gradient direction, Gdir(right).

(ii) Directional Gradient Magnitude Filter

Image gradients can be used to extract information from the images. Gradient images are created from the original image. Each pixel of a gradient image measures the change in intensity of that same point in the corresponding original image, in a specified direction. The purpose of the second step of our nodule enhancement was to modify the nodule-enhanced image into a nodule likelihood map, as illustrated in Figure 6. First, the nodule enhanced image was smoothed by using a Gaussian filter in order to reduce noise.

[Gmag, Gdir] = imgradient(I, method)

Where, Gmag - Gradient magnitude, returned as a non-sparse matrix the same size as image I.
Gdir -Gradient direction, returned as a nonsparse matrix the same size as image I. Gdir include angles in degrees within the range [-180 180] measured counterclockwise from the positive *x*-axis.

(iii) Watershed Segmentation

In the second step, the watershed segmentation was processed to detect the lung nodules accurately. To refine the rough segmentation offered by morphologic filtering, we developed a method is clustering watershed segmentation technique. Hit the highest point within the rough nodule candidate region in the nodule-enhanced image were obtained. It is used for initializing the watershed segmentation algorithm.

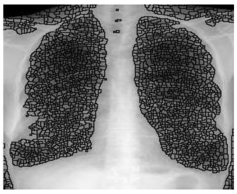


Fig.7 watershed segmentation of nodule enhanced image.

E. FEATURE ANALYSIS

We take out the features from each of the segmented nodule candidates after connected-component labeling. To analyze the texture of 2D image, the GLCM is broadly used. This GLCM matrix stores the co-occurrence frequencies of the pairs of grey levels which are grouped by a distance and orientation.

In the process of detection of nodules, the physical characteristics such as growth rate, classification pattern and margin type of the nodule plays an important role. Classifier organization depends completely on the feature selection. Feature classification includes here are contrast, energy, mean, kurtosis entropy, third moment.

Table 1 shows the texture feature extracted for first five sample image of the database**.**

Table Head	**Texture feature extraction**				
Samples	1	2	3	4	5
Mean	4.6430	4.215	5.256	6.213	4.389
Contrast	26.074	12.628	23.418	11.287	19.752
Entropy	0.853	0.724	0.861	0.623	0.731
Kurtosis	1.7043	1.5010	1.7823	1.830	1.651
Third moment	-0.227	-0.698	-0.063	-0.659	-0.078
Energy	0.5061	0.6591	0.4589	0.2560	0.5650

III. CLASSIFICATION

Classification is the process of classifying the tumor images by extracting the features of the given image suffering from the cancer and these features are compared with the features of the given sample images with help of using artificial neural network. In this process 5 sample images are given for classification and the features of these images are compared with the given image and hence lung cancer is detected. The table 1 shows the third moment, entropy, energy, mean, kurtosis and contrast extracted for first five sample image of the database.

IV. RESULT AND DISCUSSION

The proposed technique is used for many images of lungs suffering from cancer. The main objective has been achieved by the incorporation of VDE technology which can effectively detect nodules which can reduce false positive results and detect the nodule in image. In this paper texture features are extracted for the given image, features are compared with given 5 sample images for classification using artificial neural network. It is showing the images suffering with 75%, 85% and 91% of lung cancer.

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