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A Robust Technique for Detection of Lung Nodules with Virtual Dual Energy Technology and Feed Forward Neural Network

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Abstract: Lung cancer is the cause of one of the most common cancer-related deaths found in both males and females. Although attention has been paid to early stage predictions and diagnoses, prognosis is not at all working good. The two major challenges in nodule detection are to detect nodules that overlap with ribs and clavicles and also to reduce the number of false positives caused by these structures. This problem can be approached by developing more sensitive diagnosis methods using the new growing neural network technologies. In most of the existing CAD schemes for lung cancer detection by detecting the lung nodules they are not able to detect the nodules that overlap with ribs and clavicles, even though there exists VDE based CAD schemes(MTANN) with better sensitivity when compared with other schemes, it is not enough to provide high sensitivity. Here a CAD scheme incorporated with VDE scheme with FFNN that can provide better sensitivity compared to the existing techniques. This method is found to possess a sensitivity of 92.3% which is better.

Keywords: Chest radiography(CXR),virtual dual energy(VDE),feed forward neural network(FFNN),support vector machine(SVM)

1. Introduction

Lung cancer is one of the worst forms of cancer, which is the leading cause of cancer deaths in many countries [1]. Early detection of lung cancer requires too much of attention in reducing life fatalities. However, this early detection of lung cancer is not an easy task. Studies have shown that about 85% of the lung cancer cases are detected in the critical stage, so in most of the cases the option of curing by surgery is missed [2]. The 5-year survival rate is only 14%, which can reach more than 80% if lung cancer can be diagnosed in an earlier stage where lung nodules are present. This difficulty in diagnosis at the early period explains the need for an early stage prediction model [3].

Interpreting a chest radiograph is an extremely challenging task. Lung region may be superimposed with anatomical structures like heart, aorta etc. make the image more complicated, so even experienced radiologists couldn't detect subtle nodules such as nodules overlapping with ribs and, clavicles that indicate lung cancer . Chest radiography is the most frequently used diagnostic tool for chest diseases such as lung cancer, tuberculosis, pneumonia, pneumoconiosis, and pulmonary emphysema. More than 9 million people worldwide die annually from chest diseases [5]. Early detection is the most promising strategy to enhance a patient's chance of survival. Early detection can be achieved in a population screening, the most common screening for lung cancer make use of chest radiography, or Computer Tomography (CT) scans. It has been shown in the Early Lung Cancer Action Project that low-dose CT is more effective than conventional chest X-ray for the detection of pulmonary nodules [4].But CXRs are most commonly used because it is the most cost effective, most dose effective, the most routinely available and they are able to detect some unsuspected pathologic alterations.

Because of the wide use of CXRs, improvements in the detection of lung nodules in this area have a significant impact on early detection of lung cancer. But it is very difficult to find the lung nodules from the CXR by a radiologists alone. The major difficulties are as follows;(1) There is a wide range of nodule sizes, (2) nodules possess a large variation in their density and (3) nodules can be covered up by other anatomic structures. The reasons for less sensitivity may be due to difference in decision techniques, lack of clinical data, and several noise in CXRs [7],[8],[9]. For these reasons there is a particular interest for the development of computer algorithms that can serve as a second reader, highlighting suspicious regions in the radiographs that have to be judged by a radiologist.

In this paper a comparative study to evaluate the performances of various CAD schemes using as SVM classifier, Bayesian classifier [15] and FFNN has been carried out. Even though there exists several CAD schemes that utilises VDE technology [14] to detect lung nodules that overlap with ribs and clavicles, in order to improve the sensitivity further FFNN is used along with the VDE based CAD scheme. The sensitivity for CAD scheme with VDE technology and SVM classifier is found to be 76.92% , sensitivity for CAD scheme with VDE technology and Bayesian classifier is 82.69% and sensitivity for CAD scheme with VDE technology and FFNN is 92.3%.

2. Materials and Methods

2.1 Database of CXRs

In order to train the FFNN we have collected 29 cases with nodules and 23 normal cases with all the cases confirmed. For the testing of our scheme JSRT database which is publicly available is used. Instead of using the entire database only a subset of it is used.

2.2 Proposed Method

Proposed method can be represented by the following block diagram. Various steps are as follows. The input image is as shown in fig.2(a).Segmentation is carried out using Eulerminmax function which is exclusively used for the segmentation of lungs. This involves the computation of a minimum and maximum Euler numbers. Then these values are used to compute the threshold for the segmentation.VDE technology is one in which a soft tissue image is created with suppressed ribs and clavicles, which are the major source of false positives. There exists a VDE technique using MTANN. Since the neural network is very difficult to understand and difficult to be handled by the technicians in hospitals a novel approach is introduced here to create a soft tissue image with suppressed ribs and clavicles.The procedure is as follows [10];

- define a variable *'Φ'* such that it is having the same size as that of the input image and all its entries are ones.
- Make *'Φ'* to satisfy the Neumann boundary condition ie, $\frac{d\emptyset}{dt} = 0$ through several iterations.

The VDE image created is shown in fig.2(b).Next perform the region based segmentation using active contours without edges.The resulting image will be a soft tissue image in which effect of ribs and clavicles get suppressed and the nodules become visible. Next step is color based clustering. Cluster analysis or clustering is the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar (in some sense or another) to each other than to those in other groups (clusters).

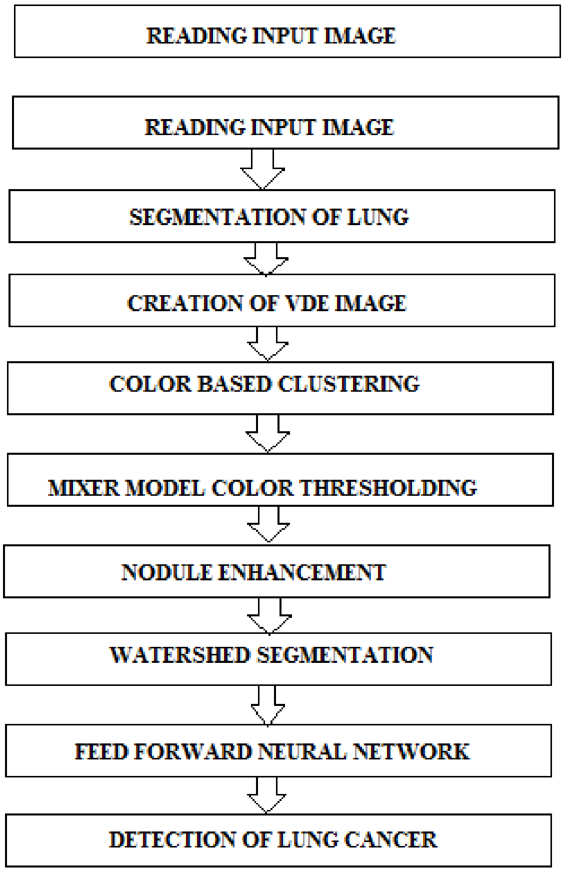


Figure 1: Block diagram of proposed method

The most common algorithm is Mean Shift Clustering Algorithm. Basic mean shift clustering algorithms maintain a set of data points the same size as the input data set. The main advantages of mean shift over k-means is that there is no need to choose the number of clusters, because mean shift finds only a few clusters.

(a) (b)

Figure 2:Examples of VDE images with ribs and clavicles suppressed using the proposed method. (a)Original CXR. (b) VDE soft-tissue image.

The mean shift algorithm is a nonparametric clustering technique which does not require prior knowledge of the number of clusters, and does not constrain the shape of the clusters. Given *n* data points , *i = 1,...,n* on a *d*-dimensional space , the multivariate kernel density estimate obtained with kernel *K(x)* and window radius *h* [11] is

$$f(x) = \frac{1}{nh^d} \sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right) \qquad (1)$$

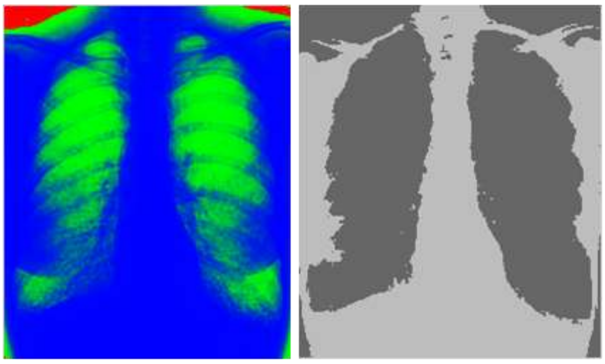
For radially symmetric kernels, it suffices to define the profile of the kernel *k(x)* satisfying

$$K(x) = c_{k,d}\ k(\|x\|^2) \qquad (2)$$

Where $c_{k,d}$ is a normalization constant which assures *K(x)* integrates to 1. The modes of the density function are located at the zeros of the gradient function $\nabla f(x) = 0$. The mean shift vector represented by;

$$m_h\,(x) = \frac{\sum_{i=1}^{n} x_i\ g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n}\ g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)} \qquad (3)$$

always points toward the direction of the maximum increase in the density. Fig.3 shows the color clustered output and the corresponding VDE image superimposed with it.



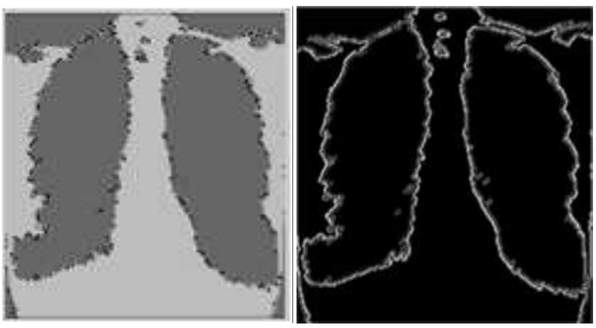
(a) (b)

Figure 3: (a) color clustered image (b) VDE image after mixer model color thresholding.

The mean shift procedure, obtained by successive

- computation of the mean shift vector $m_k\ (x^t)$
- translation of the window $x^{t+1} = x^t + m_k\ (x^t)$ is guaranteed to converge to a point where the gradient of density function is zero.

Next a two stage nodule enhancement technique is used to get the nodule enhanced image [12].The first stage uses two morphological opening operators and in the second stage the nodule enhanced image was smoothened by using a Gaussian filter to reduce the noise. In the second stage gradient magnitude and direction were calculated by using a modified sobel operator. Results of the two stage enhancement is as shown in fig. 4 .Next stage is a coarse-to-fine segmentation technique based on morphologic filtering and [12] to refine the rough segmentation provided by the morphologic filtering, a watershed segmentation technique is used.



(a) (b)

Figure 3: (a) first stage enhancement. (b)second stage enhancement.

Finally both tamura and textural features are extracted from the watershed segmented image.The tamura features are coarseness, contrast, directionality, linelikness, regularity and roughness. Coarseness is related to the size of the elements forming the texture. Contrast measures how grey levels vary and is a measure of intensity. It can be find out using the variance σ^2 and kurtosis α^4,

$$F_{con} = \frac{\sigma}{\alpha_4^n} \qquad (4)$$

$$\alpha_4 = \frac{\mu_4}{\sigma^4} \qquad (5)$$

Degree of directionality is measured from the frequency distribution of oriented local edges and their directional angles. The edge strength *e(x,y)* and the directional angle *a(x,y)* are computed as follows;

$$e(x,y) = 0.5\left(|\Delta_x\,(x,y)| + \left|\Delta_y\,(x,y)\right|\right) \qquad (6)$$

$$a(x,y) = \tan^{-1}\left(\Delta_y\,(x,y)/\Delta_x\,(x,y)\right) \qquad (7)$$

Where $\Delta_x\,(x,y)$ and $\Delta_y\,(x,y)$ are the horizontal and vertical grey level differences between the neighboring pixels, respectively. The linelikeness F_{lin} feature is defined as an average coincidence of the edge directions.The regularity feature;

$$F_{reg} = 1 - r(S_{crs} + S_{con} + S_{dir} + S_{lin}) \qquad (8)$$

where *r* is a normalizing factor and each *S* means the standard deviation of the corresponding feature that is previously extracted. The roughness feature is obtained by directly summing the coarseness and contrast measures:

$$F_{rgh} = F_{crs} + F_{con} \qquad (9)$$

Next step is to extract GLCM features [10]. An image of *GLCM (i ,j)* extracts the features based on pixel and its next neighbour pixel in the image.*GLCM (i, j)* is a two dimensional function and it is composed of *m* pixels in the vertical direction and *n* pixels in the horizontal direction, *i* and *j* are horizontal and vertical co-ordinates of the image. Basic features extracted from GLCM matrix are as follows;

Contrast: $$\sum_{i=1}^{m}\sum_{j=1}^{n}(i-j)^2\ \ GLCM(i,j) \qquad (10)$$

Energy: $$\sum_{i=1}^{m}\sum_{j=1}^{n}\ [GLCM(i,j)]^2 \qquad (11)$$

Homogeniety: $$\sum_{i=1}^{m}\sum_{j=1}^{n}\frac{GLCM(i,j)}{1+|i-j|} \qquad (12)$$

Finally FFNN [13] is trained with 20 features thus extracted (both tamura and GLCM texture) and is tested using the JSRT database.

3. Results and Performance Comparison

These same features were used to train a nonlinear SVM cassifier with gaussian kernel and is tested with a leave-one-out cross-validation test. The performance of the SVM classifier was evaluated by use of free-response receiver operating characteristic (FROC) analysis [16]. This scheme is found to have a sensitivity of 76.92%. Again these same features were used to train a bayesian cassifier and is tested with JSRT database. This scheme is found to have a sensitivity of 82.69%.Thus 20 extracted features are used to train the neural network and is tested against JSRT database. It has been found that this approach has a sensitivity of 92.3% which help to improve the survival rate of the patient.

FROC curve showing the overall performances of VDE based CAD scheme for JSRT database in a leave-one-out cross validation test with SVM classifier, VDE based CAD scheme with Bayesian classifier and original CAD scheme without VDE technology are shown in Figure 5. The performance of VDE based scheme with Bayesian classifier is found to be better than the other two. The original scheme achieved a sensitivity of 74.5%,VDE based CAD scheme with SVM classifier achieved 76.92% sensitivity and VDE based CAD scheme with Bayesian classifier achieved 82.69% . Table I:shows the comparison between various methods for lung nodule detection from CXRs.

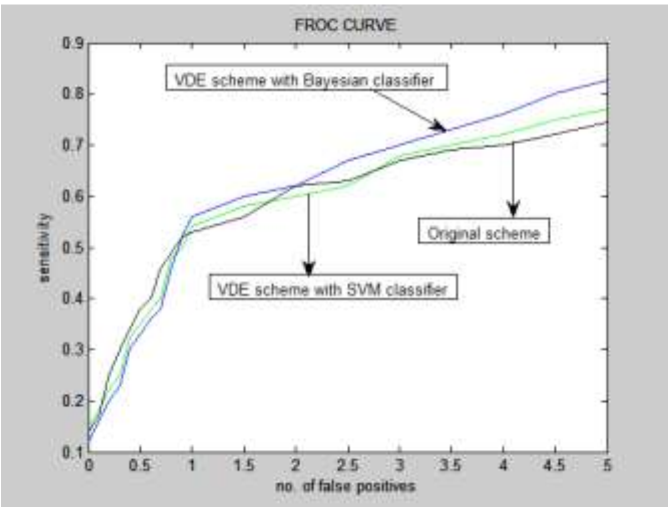


Figure 5:FROC curve indicating the performances of various CAD schemes.

Now the performance of the VDE based CAD scheme employing FFNN as pattern classifier achieved a sensitivity of 92.3% and is shown in Figure 6.

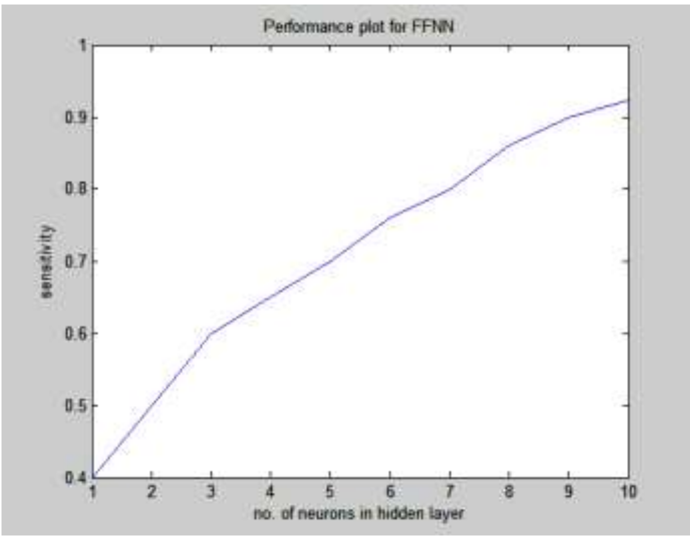


Figure 6: Performance plot using FFNN

METHOD	SENSITIVITY (IN %)
Original CAD scheme without VDE technology	74.50
VDE based method with SVM classifier	76.92
VDE based method with Bayesian classifier	82.69
VDE based method with FFNN	92.30

Table 1: Performance comparisons of various CAD schemes for JSRT database

4. CONCLUSION

We developed an advanced computerized scheme for lung cancer detection by incorporating VDE image in which ribs and clavicles are suppressed by an easier way (other than MTANN as in existing cases) with FFNN. The performance of the new approach is found to have a sensitivity of 92.3% compared with the existing techniqueVDE based CAD scheme without using a feed forward neural network.

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