Detection of Lung Nodule using Multiscale Wavelets and Support Vector Machine

K.P.Aarthy, U.S.Ragupathy

Abstract: Lung cancer is the most common and leading cause of death in both men and women. Lung nodule, an abnormality which leads to lung cancer is detected by various medical imaging techniques like X-ray, Computerized Tomography (CT), etc. Detection of lung nodules is a challenging task, since the nodules are commonly attached to the blood vessels. Many studies have shown that early diagnosis is the most efficient way to cure this disease. This paper aims to develop an efficient lung nodule detection scheme by performing nodule segmentation through multiscale wavelet based edge detection and morphological operations; classification by using a machine learning technique called Support Vector Machine (SVM). This methodology uses three different types of kernels like linear, Radial Basis Function (RBF) and polynomial, among which the RBF kernel gives better class performance with a sensitivity of 92.86% and error rate of 0.0714.

Index Terms: Lung Nodule, Multiscale Wavelets, Support Vector Machine, Wavelet Transform.

I. INTRODUCTION

The role of accurate investigation and diagnosis in the management of all diseases in medical field has become a challenging task. This is especially true for cancerous medicine. Over the past two decades, cancer has been one of the biggest threats to human life and it is expected to become the leading cause of death over the next few decades [1]. Medical imaging tests are done to find a suspicious area that might be cancerous, to learn how far the cancer has spread, and help to determine whether the treatment is effective. Lung cancer is a major concern among men and women and at present there are no effective ways to prevent lung cancer, because its cause remains still unknown. However efficient diagnosis of lung cancer in its early stages can give a better chance of recovery. The most common techniques used to detect lung tumors include chest radiography; CT scans and Magnetic Resonance Imaging (MRI). Among them, chest radiology remains the most common procedure, since it is cost effective and also the most effective diagnostic tool.

A. Lung Nodule

The various diseases associated with lungs range from common cold to pulmonary embolism, a block in the artery of lungs and an inflammatory condition called bacterial pneumonia [6]. Nodule is an abnormality that leads to lung cancer, characterized by a small round or oval shaped growth on the lung that appears as a white shadow on an X-ray or CT scan. If the growth is 3 centimeters or less, it is called a nodule and if it is larger, it is called a mass. If the size of the nodule is less than one inch (25mm), it is benign (non-cancerous) and if it is greater than one inch, it is termed malignant (cancer) [1]. The benign nodules are smooth and are of regular in shape, whereas the malignant type is rough and irregularly shaped. This lung nodule obstructs the airflow in the lungs result in breathing difficulties.

B. Lung Cancer and its Types

In 1984, the Fleischner society defined the term nodule as a lesion represented in radiograph by a sharply defined, nearly circular opacity with a diameter ranging from 2mm to 30mm. After 12 years, it is refined as a round opacity, at least moderately well marginated and not greater than 3cm in diameter. If these nodules are not diagnosed at their earlier stages, it leads to lung cancer. Lung cancer is a disease characterized by uncontrolled cell growth in tissues of the lung. If left untreated, this growth can spread beyond the lung in a process called metastasis into nearby tissue and, eventually into other parts of the body [7]. Most cancers that start in lung, known as primary lung cancers, are carcinomas that derive from epithelial cells. Each year, more number of people dies due to lung cancer than of breast, colon, and prostate cancers. The two main types of lung cancer are: Non-Small Cell Lung Cancer (NSCLC) and Small Cell Lung Cancer (SCLC).

C. Edge Detection

Points of sharp variations are often among the most important features for analyzing the properties of images which are located at the boundaries of image structures. In order to detect the contours of small structures as well as the boundaries of large objects, several researchers have introduced the concept of multiscale wavelet based edge detection. An edge in an image is the contour across which the brightness of the image changes abruptly. Edge detection is an important tool in pattern recognition and image segmentation [6]. If the edges in an image are identified accurately, all of the objects can be located and basic properties such as area, perimeter and shape can be measured.

D. Support Vector Machine

SVM is a machine learning tool, based on the idea of data classification. It performs classification by constructing an N-dimensional hyper plane that optimally separates the data into two categories. The separation of data can be either linear or non-linear. Kernel function maps the training data into a kernel space and the default kernel function is the dot product. For non-linear cases, SVM uses a kernel function which maps the given data into a different space; the separations can be made even with very complex boundaries.

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The different types of kernel function include polynomial, RBF, quadratic, Multi Layer Perceptron (MLP). Each kernel is formulated by its own parameters like γ, σ, etc. By varying the parameters the performance rate of the SVM can be measured.

Stephane Mallat and Sifen Zhong [12] proposed a method using multiscale edge detection through wavelet theory. The wavelet local maxima across scales characterize the local shape of irregular structures. Numerical descriptors like magnitude and angular values of the gradient vector are derived. According to P.Korfiatis et al., the concept of multiscale wavelet for highlighting lung border edges is proposed. Durgesh K.Srivastava and Lekha Bhambhu proposed SVM technique for data classification. From the literatures it is observed that the lung nodule must be detected accurately. In this paper, segmentation of lung nodule based on multiscale wavelet based edge detection and morphological operations; classification of lung nodules using SVM is proposed.

This paper is organized into three different sections including this introduction to lung cancer and the discussion of the existing techniques. In section II the technique for segmentation of the lung nodules is proposed, which includes the edge detection using multiscale wavelets and the morphological filtration. Section III gives a description about SVM, its classification methodology using different types of kernels. Conclusion and future scopes are drawn in section IV.

II. PROPOSED METHOD

The proposed method for segmentation of lung nodules is shown in Fig.1. The lung nodule images are taken from the Lung Image Database Consortium (LIDC) and an image with lung nodule is shown in Fig.2.

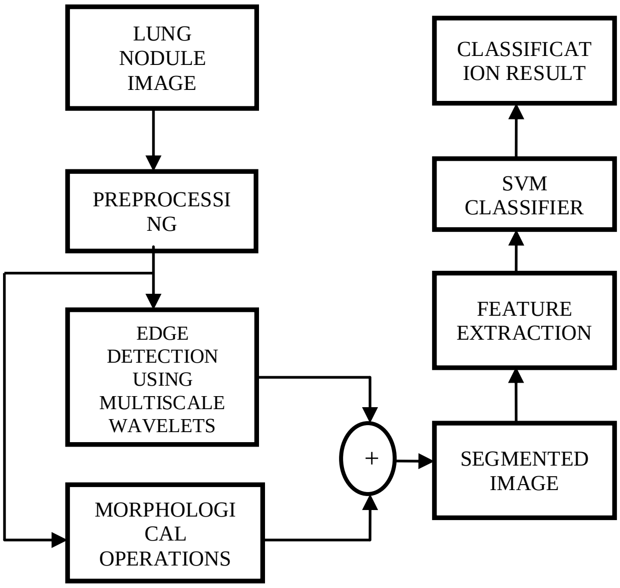


Fig.1. Block Diagram of the Proposed Nodule Detection Scheme

The image is allowed for pre-processing and the edges of the threshold binary image are detected by multiscale edge detector using Wavelet Transform (WT). Morphological operation is performed on the preprocessed image and the output of the mathematical morphological operation is summed up with the edge detected image to obtain the segmented lung nodule image.

Fig.2 Lung Image with Nodule

A. Multiscale Edge Detection

Edge detection is one of the most important steps in image processing and computer vision. Sound edge detection can provide valuable information for further image processing such as image segmentation, image enhancement and image compression.

The two important features of the edge pixels are:

1. Edge strength: Magnitude of the gradient
2. Edge direction: Angle of the gradient

The sharp variations in the images are located at the boundaries of larger objects and in order to detect these edges a technique called multiscale edge detection is introduced. Wavelets overlying the edges yield large wavelet coefficients; wavelets overlying a smooth region yield small coefficients [3]. Multiscale edge detectors smooth the signal at various scales and are used to identify the sharp variation points. The scale defines the size of the neighbourhood, where the signal changes are computed. The WT is closely related to multiscale edge detection. Canny edge detector is a method which is used to find the local maxima of the WT modulus [4].

B. Multiscale Wavelet Transform

The WT is used to position the high frequency details which are considered as the discontinuous points in edge detection, thereby extracting the edges of images [11]. Edges of the suspicious mass region are calculated using multiscale wavelet based edge detector. The multiscale edge detection is done through the WT defined with respect to two wavelets $W^1_{2^j} f(x,y)$ and $W^2_{2^j} f(x,y)$ which are the horizontal and vertical filtered components. A combination of WT and multiresolution works better for edge detection [10].The wavelet transform of image f(x, y) at the scale 2^j has two components defined in equations 1 and 2 given below.

$$W^1_{2^j} f(x,y) = f * \psi^1_{2^j} f(x,y) \qquad (1)$$

$$W^2_{2^j} f(x,y) = f * \psi^1_{2^j} f(x,y) \qquad (2)$$

The WT of the image has two filtered components at different scales. Fig.3 shows the two derivatives of the wavelet components.

$W^1_{2^j}$ $\qquad\qquad$ $W^1_{2^j}$

Fig.3 Wavelet Derivative Components at Eight Different Scales

In Fig.3, the first row represents the original image and the remaining are the wavelet derivative components, $W^1{}_{2}{}^{j}$ and $W^2{}_{2}{}^{j}$ of the image at eight different scales for $1 \leq j \leq 8$. The image gets deformed for scales larger than 2^6.

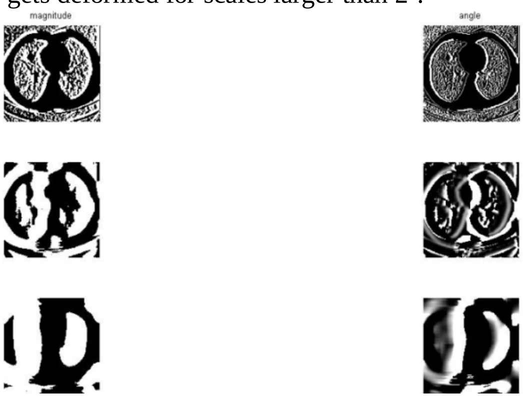


Fig.4 Magnitude and Angular Images

The two wavelet components shown in Fig.3 are given as inputs to the modulus maxima equation 3 and the angular equation 4, the edges are detected and the edge detected outputs at three different scales are shown in Fig.5. The two components of the wavelet transform are used to find the modulus and angle of the gradient vector. Fig.4 shows the magnitude and the angular images obtained at different scales with the wavelet derivative components using the equations 3 and 4. At each scale 2^j, the modulus of the gradient vector is given by,

$$M_{2^j} \, f(x, y) = \sqrt{|W_{2^j}^1 \, f(x, y)|^2 + |W_{2^j}^2 \, f(x, y)|^2} \quad (3)$$

The angle of the gradient vector with the horizontal direction is given by,

$$A_{2^j} f(x, y) = \arg\left(W_{2^j}^1 \, f(x, y) + \mathrm{i} \, W_{2^j}^2 \, f(x, y)\right) \quad (4)$$

(a) (b) (c)

Fig.5: Edge Detected at Different Scales: (a) Scale1 Edge (b) Scale2 Edge (c) Scale3 Edge

The sharp variation points of $f * \theta_{2^j}$ where $\theta(x, y)$ is the smoothing function are the points (x, y) where the modulus $M_{2^j} \, f(x, y)$ has local maxima in the direction of the gradient given by $A_{2^j} f(x, y)$ [12]. The edges can be detected for eight different scales, in which the edge at scale 2 gives better result. The position of the modulus maxima and the angle at the corresponding locations are recorded. By making use of the modulus and the angle of the gradient vector equations, the edges of the mass regions are obtained. With the multiscale wavelet based edge detection concept, edges of the suspicious mass regions are obtained at different scales [14].

C. Morphological Operations

The morphological operation includes dilation, erosion, opening and closing. These operations are carried out to enhance the edges by removing the distortions produced from multiscale wavelets. The final morphological filtered output image obtained by different operations like dilation, filling, and erosion is shown in Fig.6. The non-spherical shaped nodules are detected by using Anti-geometric diffusion and Rule-based techniques [13].

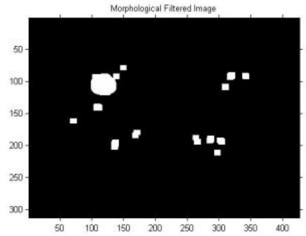
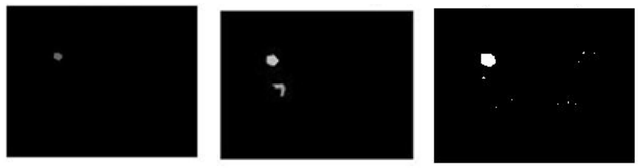


Fig.6 Morphological Filtered Image

D. Segmentation

Segmentation is the most crucial and challenging step in the analysis of lung nodules. Nodules are frequently attached to other structures, including the local pulmonary vasculature and the pleural surface adjoining thoracic wall. Segmentation is the final step in detection of suspicious region. It is concerned with dividing the image into meaningful region. Segmented image is obtained by adding the edge detected output with the morphological filter output. The lung nodule segmentations carried out by the addition of wavelet based edge detection and the morphological filtering are shown in Fig.7. The segmentation of lung nodules is carried out with different structuring elements and it is observed that the spherical SE gives better segmentation result than the other types.



(a) (b) (c)

Fig.7: Segmented Lung Nodule Images: (a) Ball SE_9 (b) Disk SE_9 (c) Sphere SE_9

The nodule segmentation results are shown in Fig.7, in which the nodule clearly displayed in Fig.7(c), which is obtained using sphere SE [9]. The next step is classification of lung nodules as normal/abnormal which is carried out using a machine learning technique called SVM, which is discussed in the subsequent section.

III. CLASSIFICATION USING SUPPORT VECTOR MACHINE

SVM is a machine learning technique which is used as a classification tool. It uses kernel function, which acts upon the input data; final summation with an activation function gives the final classification result. The architecture of SVM is shown in Fig.8, in which the suffix 'n' represents number of vectors. N_s denote the number of support vectors. A binary classification [2] is used here, in which a hyper plane classifies the given data into two different classes; the vectors closest to the boundaries are called support vectors and the distance between the support vectors and hyper plane is called margin.

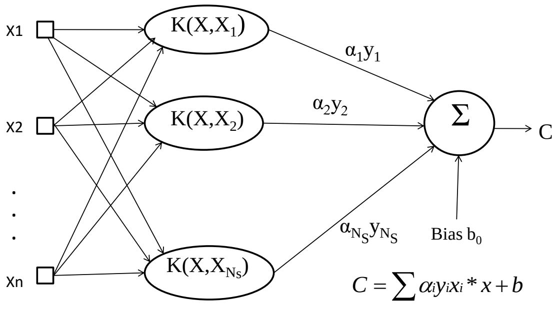


Fig.8 Architecture of SVM

SVM uses different types of kernels like linear, polynomial and RBF. Their formulations are given in the equations 5-7, in which the term "K(Xi,Xj)" represents the kernel function; Xi and Xj are the vectors under classification.

$$K(Xi,Xj) = Xi^T Xj \quad (5)$$

$$K(Xi,Xj) = (\gamma Xi^T Xj + r)^d \quad (6)$$

$$K(Xi,Xj) = exp(-\gamma \|Xi - Xj\|)^2 \quad (7)$$

In the above kernel function types, 'γ'and'd' are the kernel parameters, whose values are '1' and '3' respectively. There are also different types of methodologies available for finding the hyper plane, such as Quadratic Programming, Sequential Minimal Optimization (SMO) and least square technique. Totally, 28 lung images are taken from the LIDC database which includes 15 non-cancerous and 13 cancerous types. Among the 28 image dataset, only 10 are given in the Table. I, first 5 are cancerous and the next 5 are non-cancerous data.

A. Feature Extraction

The features extracted from the lung images are mean, contrast, entropy and standard deviation. Mean value denotes the average value of all the pixels. Contrast is a measure of the intensity between a pixel and its neighborhood of the image.

$$\text{Contrast} = \sum_{i,j} |i-j|^2 p(i,j) \quad (8)$$

i,j denotes the row and the column pixel

$$\text{Standard deviation} = \left(\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2 \right)^{\frac{1}{2}} \quad (9)$$

Where, $\bar{x}$ is the mean value and n is the number of elements in the sample.

Entropy is a statistical measure of randomness, used to characterize the textural properties of input image. It is given by,

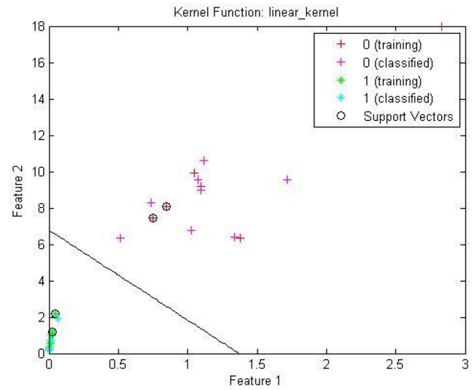
$$\text{Entropy} = (p.*\log 2(p)) \quad (10)$$

where 'p' is the input image.

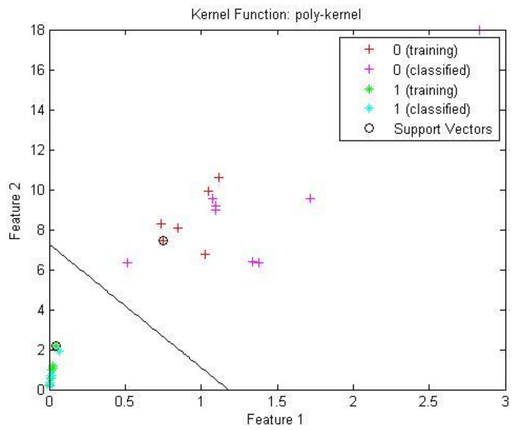
TABLE I. COMPARATIVE ANALYSIS OF DIFFERENT TYPES OF SVM KERNELS

CANCER/NON -CANCER	MEAN	SD	CONTRAST	ENTROPY
CANCER	0.156	0.7087	4.36E-04	0.1189
CANCER	0.189	0.9479	8.41E-04	0.4187
CANCER	0.117	0.685	2.22E-04	0.3091
CANCER	0.2487	0.2188	1.15E-04	0.2055
CANCER	0.3941	0.2483	1.38E-04	0.2089
NON-CANCER	2.5926	16.1686	0.0968	0.5335
NON-CANCER	2.8307	17.9556	0.0912	0.7786
NON-CANCER	1.7206	9.5487	0.0159	0.6959
NON-CANCER	1.1144	10.5823	0.0459	0.3189
NON-CANCER	1.3799	6.345	0.0165	0.4306

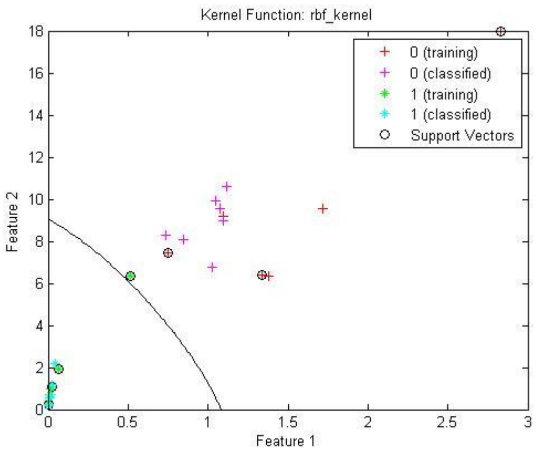
The classification results obtained by using three different kernel types are shown in Fig.9. Among the various features extracted, the selected features include mean and standard deviation, as they vary in their values between the cancerous and non-cancerous images [15].



(a)



(b)



(c)

Fig.9: Lung Cancer Data Classification using SVM Kernels: (a) Linear, (b) Polynomial (c) RBF

From the Fig.9, it is observed that the SVM classification is performed using three different kernels, in which the X-axis represents feature 1(mean) and the other feature (standard deviation) is represented in the Y-axis. The hyper plane divides the data into two classes, called binary classification. The binary value '0' denotes non-cancerous data and the value '1' represents the cancerous data. The distance between the hyper plane and the support vectors is called margin. The statistical resultant data obtained by using three different types of kernels using SVM is compared in Table II.

TABLE II. COMPARATIVE ANALYSIS OF DIFFERENT TYPES OF SVM KERNELS

TYPE OF THE KERNEL	CP	SENS	SPEC	ERROR RATE	BIAS
Linear	85.71%	82.6%	71.43%	0.142	0.8620
Polynomial	78.57%	57.1%	78.5%	0.214	0.8011
RBF	92.86%	86.2%	85.71%	0.071	0.4142

CP: Class Performance, SENS: Sensitivity, SPEC: Specificity

From the Table II, it is seen that the RBF kernel gives better performance with less error rate than the other two types of kernels. The 'bias' term represents intercept of the hyper plane that separates two different groups of data, the smaller the bias value the better the classification performance.

III. CONCLUSION

In this paper, a novel segmentation technique based on multiscale wavelet based edge detection and morphological operations is carried out for lung cancer images. The idea of multiscale wavelets to identify the sharp variation points in the lung image is introduced. Then classification of lung nodules as normal/abnormal is done by using SVM. In this paper, it is shown that RBF kernel gives better classification performance of 92.86% with an error rate of 0.0714. The future work is to do the classification performance by using multi-class classifier type.

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