

RESEARCH ARTICLE



ISSN: 2321-7758

ANFIS METHODOLOGY FOR LESION DETECTION AND CHARACTERIZATION IN THORACIC IMAGES

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Article Received: 02/05/2015

Article Revised on:08/05/2015

Article Accepted on:12/05/2015



ABSTRACT

Lung tumor detection and lung tumor characterization in CT-lung image is done by context driven approximation method(CDA).The method for lung tumor detection includes pre-processing, feature extraction, lung tumor classification. The CDA methodology plays a vital role in lung tumor detection and lung tumor characterization. CDA methodology detect lung tumor and involvement of lymph nodes. First for given input lung CT-image preprocessing is carried out. The Grey Level Co-occurrence Matrix(GLCM) feature extraction mechanism is done to get the repeated patterns occurring in an image. The GLCM features includes energy, contrast, correlation, homogeneity, entropy, etc. After extracting features lung tumor detection is carried out through sparse representation mechanism by which low contrast between tumor and non tumor cells are detected by means of spatial consistency constraints. Then the lung tumor characterization is carried out through multi atlas mechanism based on appearance constraints. The performance accuracy for lung tumor detection area is measured through parameters such as true positive, false positive, false negative, recall, precision and f-score to measure.
Keywords: *CT, lung tumors, GLCM, ANFIS*

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INTRODUCTION

The lung cancer is the second most commonly diagnosed cancer and the lung is a most common spot of metastasis from other cancers that is clear as pulmonary nodules. The CT is the most discerning diagnostic imaging modality for the recognition of lung cancer and the declaration of any unclear abnormalities detected on chest radiographs. Recently, CT techniques have been applied to be promising for detection of early lung cancers in high-risk populations and have been shown to be promising for detection of early lung cancers.

A similar question arises in the context of primary lung cancer detection. Lung cancer, i.e., the primary bronchial carcinoma is the leading cause of cancer death [1]. Lung cancer is the type of uncontrolled growth of abnormal cells in one lung or both lungs. These abnormal cells will not function like normal cells and they affect healthy lung tissue. The growth of the abnormal cell can form tumors. The tumor cell interfere with the normal functioning of the lung, which provides oxygen and blood to whole body.

Two major types of lung cancers are
Non Small Cell Lung Cancer(NSCLC)

Small Cell Lung Cancer(SCLC)

In particular, non small cell lung cancer (NSCLC) is the most prevalent type of lung cancer, accounting for about 80% of all cases [2]. For NSCLC, the tumor node metastasis (TNM) staging is the internationally agreed system, which involves analysis of the primary lung tumor, regional lymph nodes and distant metastases[2].

RELATED WORK

An automatic pulmonary lesions are detected by using segmentation based partial volume analysis. Usually lung CT-image not only contain lung region but also it contains other background region such as heart, liver and other region. First for the input image bit plane slicing algorithm is applied to get sharpened image and better accuracy. Then they used median filtered algorithm to remove noise from the image for further processing. Then segmentation of pulmonary lesion is carried out using flood fill algorithm to obtain lung border region alone from the image. Then segmentation based partial volume analysis is carried out using morphological method. Initial segmentation is carried out using region growing algorithm, morphological erosion is carried out by applying lower threshold value that is referred as erosion threshold. More number of vessels is connected to nodule region that is detected using with no existence of optimal erosion strength that is computed by nodule region connected to neighborhood region. After Boundary refinement is process to connect convex nodules, there is more injured are than the nodule tissue. Some number of nodules are identified manually but, there some other affected nodules which are not identified is also presented in the lung field that remaining nodules are identified using this mechanism. The partial volume analysis method accuracy is higher than the mask voxel volume.

characterization of lung tissue pattern by proposing near affine texture descriptor in high resolution computed tomography imaging. Grey level histogram is applied to find the lung tissue pattern. Then wavelet transform is applied to find the near affine texture features. Translation invariance, Rotation Invariance, and Scale Covariance are applied to the image to perform wavelet transform by which lung tissue analysis is carried out. From the normalized histogram mean, standard deviation and

frequent patterns are obtained. Then texture analysis or pattern features in the image is extracted using discrete wavelet transform. Then extracted features are combined by means of wavelet coefficient to categorize the lung tissue pattern. This method provides accurate description about textures that do not contain any prevailing orientations. Then the characterization of biomedical tissues is carried out related to texture features, they also provide wide variety about textures analysis and the proposed method allows a global classification accuracy of 76.9% with balanced precision among five classes of lung tissue using a leave-one-patient-out cross validation, in accordance with clinical practice.

The identification and characterization of diffuse parenchyma lung disease (DPLD) and challenges in patterns in computed tomography(CT) lung analysis. In this work multi-detector CT(MDCT) is used it's a high resolution CT. For preprocessing two algorithms are used, one is histogram thresholding for lung region segmentation by interstitial pneumonia pattern and edge highlighting wavelet preprocessing is carried out to detect lung region edges. Vessel tree segmentation algorithm is used to detect the structure of the vessel tree and to reduce the false positive detections of vessels. Feature extraction is carried out using grey level co-occurrence features, the features such as contrast, correlation, entropy are extracted. The sum average, sum variance, sum entropy, difference variance, difference entropy are measured. The mean and variance are measured according to co-occurrence matrix. Then by using NN classifier statistical pattern recognition is carried out. K-NN classifier is used to classify the interstitial pneumonia patterns by comparing trained feature set with test feature set by selecting number of nearest neighbors based on correct classification rate. The texture patterns are challenged by false positives due to similarity in vessel tree structure. The differentiation between the normal and tumor patterns are identified by increasing number of normal training pattern. Performance evaluation is carried out through identifying and characterizing the pattern through volume overlap, true positive pattern and false positive pattern on five MDCT scans.

PROPOSED WORK
System Architecture

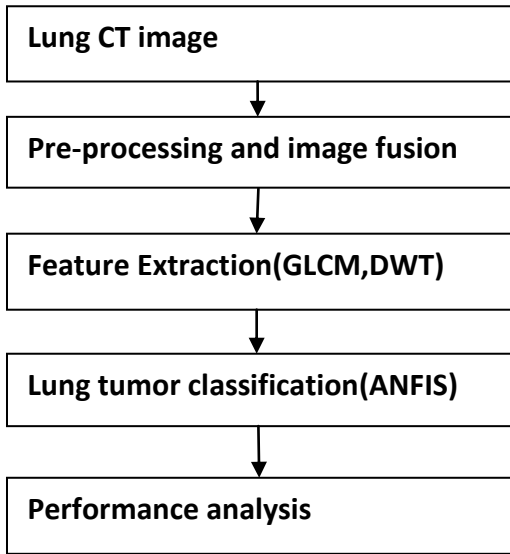


Figure 1: System Architecture

A. Preprocessing

Preprocessing of CT Lung image is the first step in the proposed technique. Preprocessing of an image is done to reduce the noise and to enhance the image for further processing. The main purpose of this step is basically to improve the image quality for further processing as to get more surety and ease in segmenting the Lung Region alone.

A 3x3 median filter is applied to the whole input lung CT image in order to remove the noise from the image.

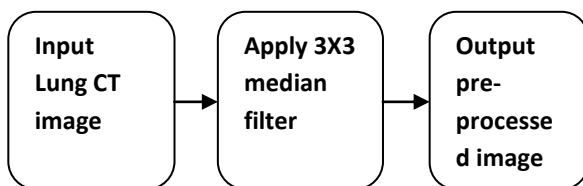


Figure 2: preprocessing

After preprocessing image resizing is carried out as 256X256 in-order to process the image for further processing.

The term fusion means is an approach to extract information acquired in several domains. The goal of image fusion (IF) is to integrate complementary multi view information into one new image containing more information. Input lung image and tilted lung image are fused using fuzzy logic according to pixels.

B. Feature Extraction

GLCM

The GLCM is a tabulation of how often different combinations of pixel brightness values (grey levels) occur in an image. The Order of glcm matrix is used for series of calculations. First order measures are statistics calculated from the original image values, like variance, and that do not consider pixel neighbor relationships. Second order measures consider the relationship between groups of two (usually neighboring) pixels in the original image. Third and higher order textures (considering the relationships among three or more pixels) are theoretically possible but not commonly implemented due to calculation time and interpretation difficulty. There has been some recent development of a more efficient way to calculate third-order matrices. Frame work of glcm matrix considers the relation between two pixels at a time, called the reference and the neighbor pixel. The neighbor pixel is chosen to be the one to the east (right) of each reference pixel. This can also be expressed as a (1, 0) relation: 1 pixel in the x direction, 0 pixel in the y direction. Each pixel within the window becomes the reference pixel in turn, starting in the upper left corner and proceeding to the lower right. Pixels along the right edge have no right hand neighbor, so they are not used for this count.

The extracted GLCM features are

- Energy
- Contrast
- Homogeneity
- Correlation

GlcM matrix is formed from the original image matrix. By determining the maximum value in image matrix, glcm matrix can be formed. if the maximum value of the image matrix is 5, then glcm matrix should be in the order of 5X5. The glcm matrix is set to angle of 45, so that the diagonal elements are compared and the repetition of elements are noted. The number of occurrences of repetition forms glcm matrix. The glcm matrix and image matrix are shown as below. Image matrix

1	5	3	4
2	2	4	1
3	4	5	5
4	2	1	2

In the above matrix, the maximum value obtained is 5, hence the glcm matrix is formed in the order of 5X5.the glcm matrix is shown as below. Glcm matrix

GlcM	1	2	3	4	5
1	0	1	0	0	0
2	0	0	0	1	1
3	0	1	0	0	0
4	1	0	0	0	1
5	0	1	0	1	0

In glcm matrix the values of ones and zeros are formed based on image matrix. As the glcm matrix is at an angle of 45 degree, the diagonal elements are compared,(1,1) pair does not occur diagonally, hence it takes the value 0.The ordered pair (1,2) occur only once diagonally, hence it takes the value 1.thus glcm matrix is formed. The glcm features includes angular spread of power estimation prevents the effects of high-frequency noise. The band of frequencies to be excluded (i.e., the nonlinear portion) was selected based on experimentation using synthesized images with known values, and also using a number of Region of interest(ROIs) obtained. The range of pixels is in discrete representation.The glcm power done in frequency domain is ignored. Angular spread of power is done for obtaining parametric representation of multidirectional oriented patterns. It generates the features of spiculated patterns. The spread of power is limited to smaller number of angular bands.

DWT

Most of genes are not relevant to the distinction between cancerous and normal tissues. Finding small gene sets that are sufficiently informative to distinguish between cells of different types is a requirement of diagnosis in practice. Furthermore, it is very important to pathologist to isolate genes which are potentially intimately related to the tumor makeup and pathomechanism [8]. From classification point of view, reduction the dimension of the feature space can help overcome the risk of over fitting. Over fitting problem arises frequently in tissue classification problem where the dimension of the feature vectors (in our case thousands of genes) is typically several orders of magnitude larger than the number of training patterns (in our case a few dozen tissue samples). In such a situation, classification performance on a test set is much more poor than on training set.

C. ANFIS Methodology

Adaptive Neuro Fuzzy Interference Systems (ANFIS) are adaptive networks implemented in MATLAB software. An adaptive network consists of a group of nodes and directional links. The network has a learning rule such as back propagation. ANFIS is said to be adaptive the nodes have parameters which influences the output node. ANFIS is a supervised learning technique and relates the inputs with the outputs. ANFIS uses a hybrid learning algorithm to identify the membership function parameters of single-output. The network has a learning rule such as back propagation. ANFIS is said to be adaptive the nodes have parameters which influences the output node. ANFIS is a supervised learning technique and relates the inputs with the outputs. A combination of least-squares and back propagation gradient descent methods are used for training membership function parameters to model a given set of input/output data. An Automated classification and detection of tumors in different medical images demands high accuracy since it deals with human life. Different approaches that can produce medical images must be studied. Also, the technique that produces those images is very important in order to know what to apply to a certain medical image in order to get better results.

D. Performance Analysis

For lesion detection and characterization six parameters are used to analysis the performance

- True positive (TP)
- False positive(FP)
- False negative(FN)
- Recall
- Precision
- F-score

True positive is an annotated lesion that was correctly identified and the volume of the detected lesion overlapped the ground truth annotation by at least 50% false positive is an extra lesions that was detected and false negative is an annotated lesion that was not detected, or the overlap between the detected volume and the annotated volume was smaller than 50%. The overlap formula and the 50% threshold were applied following the PASCAL standard for evaluating object detection.Then recall, precision, F-score are calculated using the formulas

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

$$F\text{-score} = \frac{2TP}{(2TP + FN + FP)}$$

Experimental Results

Input

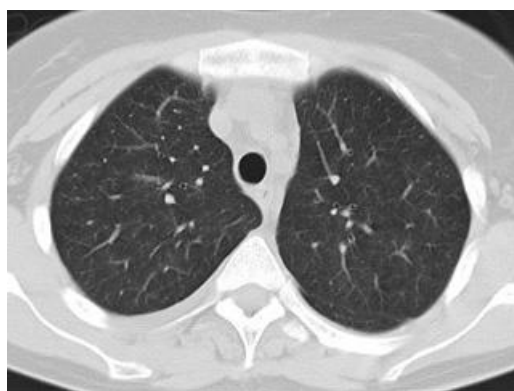


Figure 3: Input Lung CT image

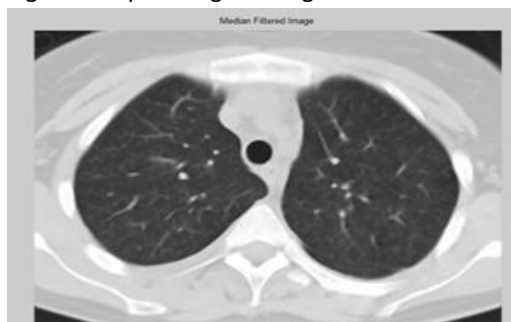


Figure 4: Preprocessed image

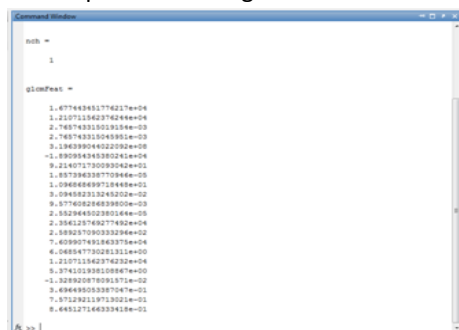


Figure 6: GLCM Feature extractions

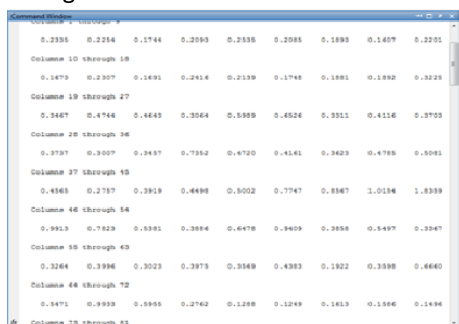


Figure 7: DWT Feature extraction

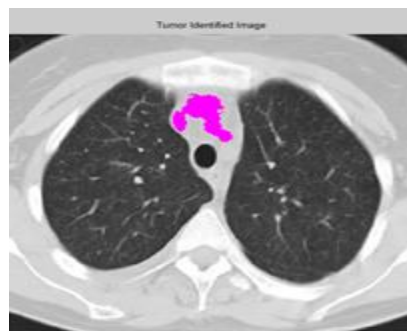


Figure 7: Tumor detected image

Image	Se	Sp	Acc
Column 1 through 3			
1.00000000000000e+00	1.450832819247378e+00	9.931293543519461e-01	
2.00000000000000e+00	1.273764787752262e+00	9.993447635688544e-01	
Column 4 through 6			
0	0	9.766235351562500e-01	
0	0	9.9012754347636251e-01	
ans =			
Avg: 1.362299 0.994237 0.983376			
/s >>			

Figure 8: Performance measure

Conclusion

The lung tumor diagnosis is an important criteria in medical field. Lung tumor area is detected from lung CT image. The detected lung tumor can be diagnosed using ANFIS classifier. Then the lung tumor are classified as benign or malignant. The performance analysis is carried out in terms of sensitivity, specificity, positive predictive value, negative predictive value and Accuracy. Sensitivity (true positive fraction) is the probability that a diagnostic test is positive, given that the person has the ischemic stroke disease. Specificity (true negative fraction) is the probability that a diagnostic test is negative, given that the person does not have the disease. The high accuracy is achieved for tumor region in accordance with ground truth images.

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