Region Based Mass Estimation Technique Based Image Segmentation for Lung Cancer Detection Using Gabor Filters

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ABSTRACT: Lung cancer detection is a dominant research in medical image processing, where there exists various solutions for lung cancer detection but suffers with the problem of accuracy and false positive results. We propose a naval approach for lung cancer detection which segments the image using region based mass estimation with the support of gabor filters. The proposed approach enhances the image by applying Gabor filter as the preprocessing task. The preprocessed image is applied with edge detection technique using sobel edge detector. The detected edges are used to extract the regional properties and for each distinct region, we estimate the white mass value based on the gray values of the image pixels. The estimated gray mass value is used to segment the image, we segment the image based on the gray mass. The proposed approach performs lung cancer detection using the estimated mass value and the average gray value of the region which has more mass value. The proposed approach has produced efficient results with more accurate lung cancer detection. The approach has produced less time complexity with higher accuracy.

Key Terms: Lung Cancer Detection, Region Based approach, image segmentation, Gabor Filters.

1. INTRODUCTION

The lung cancer the most dangerous threat to the human life and the detection of presence of disease has to be identified at the early stage. To perform detection of lung cancer the medical researchers perform various activities and methodologies. The preliminary diagnosis approach is identifying the presence of disease from normal X-ray images. The quality of X-ray image is low and has to be improved for its clarity before performing identification. To support medical domain around this problem there are many researchers working on this.

The lung image has various regions like black pixels region and white pixel region which has to be identified. The various regions present in the image has to be identified using which the lung cancer detection has to be performed. There are many components in the lung image like left and right lung and a middle hose which connects both of them. In an X-ray image, the left and right lungs are visible in black color and other are visible in white pixel. From the above details, we have to identify the various region of the lungs with different features using some edge detection techniques and gray values. This region based approach can be used for segmentation of various features to identify the presence of lung cancer and its location.

The segmentation is the process of grouping similar featured pixels of an image into one and representing different featured pixels in different forms or colors. The segmentation process can be used in various tasks where the classification is necessary to perform a particular task. The segmentation techniques uses various metrics to separate the pixels from others, for example color values, region
properties and etc. The segmentation techniques have been used for variety of medical problems and produces good results for most cases. Whatever the scans used to diagnose, the medical practitioner could not identify or locate a region exactly where the cancer present or he may ignore the presence of cancer. This is where segmentation plays and performs grouping of pixels and deviates them from other normal pixels to identify lung cancer.

The input image contains noise, blur so that the image has to be noise removed. The Gabor filter is the most efficient linear filter which could be used to remove noise from the image. The noise removed image can be further segmented to achieve the task of segmentation. We use the Gabor filter at different levels to get the quality image from the input image.

The input X-ray image contains noise and blurs, so that it has to be removed to achieve the required results. We compute mass estimation here, where the mass estimation is the process of computing the gray level density value or mass. The region of cancer affected pixels must have more gray levels and the mass of gray co-efficient will be higher in that region. We use this property of pixels to identify the location of lung cancer.

2. RELATED WORKS

There are number of approaches has been discussed in literate to identify lung cancer in the X-ray images, we discuss few of them in this paper.

A Novel Approach of Cancerous Cells Detection from Lungs CT Scan Images [1], uses sobel edge detector to enhance the image. The enhanced image is binaries and they generate label matrix which labels each object and they perform reordering of objects. Then region of interest is identified and edge detection is performed to identify the lung cancer.

Lung Nodule Detection in CT Images Using Thresholding and Morphological Operations [2], has two stages: lung region segmentation through thresholding and then segmenting the lung nodules through thresholding and morphological operations.

Methylation analysis in spontaneous sputum for lung cancer diagnosis [3], proposes A novel risk analysis is introduced, using the distinction between diagnostic and risk markers. Two independent sets were randomly composed from a prospectively collected sputum bank (Set 1: n = 98 lung cancer patients, n = 90 controls; Set 2: n = 60 lung cancer patients, n = 445 controls). Sputum cytology was performed for all samples. The following DNA hypermethylation markers were tested in both sets: RASSF1A, APC and cytoglobin (CYGB). Two statistical analyses were conducted: multivariate logistic regression and a risk classification model based on post-test probabilities.

Molecular profiling of small cell lung cancer in a Japanese cohort [4], conducted the present Shizuoka Lung Cancer Mutation Study to analyze genomic aberrations in patients with thoracic malignancies. We collected samples of SCLC from a biobank system and analyzed their molecular profiles. We assessed 23 mutations in nine genes (EGFR, KRAS, BRAF, PIK3CA, NRAS, MEK1, AKT1, PTEN, and HER2) using pyrosequencing plus capillary electrophoresis. We also amplified EGFR, MET, PIK3CA, FGFR1, and FGFR2 using quantitative real-time polymerase chain reaction (PCR) and the fusion genes ALK, ROS1, and RET using reverse transcription PCR.

Automated lung cancer detection by the analysis of glandular cells in sputum cytology images using scale space features [5], develop an automated lung cancer detection system which segments the cell nuclei and classifies the glandular cells from the given sputum cytology image using a novel scale space catastrophe histogram (SSCH) feature. Catastrophe points occur when pair wise annihilation of
extreme and saddle happens in scale space. Unusual nuclear texture shows the presence of malignancy in cells, and SSCH-based texture feature extraction from nuclear region is done. From the input high-resolution image, the cellular regions are localized using maximization of determinant of Hessian, nuclei regions are segmented using K-means clustering, and SSCH features are extracted and classified using support vector machine and color thresholding.

Cell extraction from sputum images for early lung cancer detection [6], proposes two different methods, namely, a Rule-based method, and Bayesian classification. We describe the two methods and we compare their performances in terms of their behaviors with respect to color representation and color quantization.

A novel assignment of various bioimaging methods for lung tumor detection and treatment using 4-D and 2-D images [7], describes fully Automatic Decision Support system for Lung Cancer diagnostic from CT Lung images. Most traditional medical diagnosis systems are founded on huge quantity of training data and takes long processing time. However, on the occasion that very little volume of data is available, the traditional diagnosis systems derive defects such as larger error, Time complexity. Focused on the solution to this problem, a Medical Diagnosis System based on Hidden Markov Model (HMM) is presented. They describe a pre-processing stage involving some Noise removal techniques help to solve this problem, we preprocess an images (by Mean Error Square Filtering and Histogram analysis) obtained after scanning the Lung CT images. Secondly separate the lung areas from an image by a segmentation process (by Thresholding and region growing techniques). Finally they developed HMM for the classification of Cancer Nodule. Detection of lung tumor in CE CT images by using weighted Support Vector Machines [8], propose a novel method for assigning optimal weights for the calculated features. This proposed technique is tested on CE CT Lung images.

The above discussed approaches are struggles with detection accuracy and false positive results and we propose a naval approach for lung cancer detection which works based on region based mass estimation technique.

3. PROPOSED METHOD

The proposed method has various stages namely preprocessing - where the quality of the image is improved, Edge detection - where the distinct regions are identified, mass estimation – the white mass values of the region is estimated and segmentation - which performs grouping of pixels and finally lung cancer detection.
3.1 Preprocessing:

The input image is preprocessed to remove the noise presence in the image and increase the image quality which supports the segmentation process. We apply Gabor filter to remove the noise content from the image which performs noise removal in iterative manner. We apply the Gabor Filter with different frequency and orientation to extract the features of the image. This stage removes defects caused by the image acquisition process, for example, noise and lack of contrast. The preprocessed image is used for further processing to identify the lung cancer.

Algorithm:

Input: Image I.

Output: Enhanced Image EI.

Step1: Initialize sinusoid factor $\lambda$, Orientation O, and phase offset $p$, standard deviation $sd$, gamma.

Step2: for each pixel $P_i$ from $I$

compute $\sigma_X = \gamma$.

compute $\sigma_Y = \lambda /\gamma$.

compute x axis rotation $X_r$.

compute y axis rotation $Y_r$. 
\[ \text{Ga} = \exp(-0.5*(Xr^2/\sigma_X^2+Yr^2/\sigma_Y^2))*\cos(2*\pi/sd*Xr+p); \]

Restore \( \text{Pi} = \text{Pi} - \text{Ga} \).

end

step3. Stop.

### 3.2 Edge Detection:

The preprocessed image is used for edge detection to support segmentation process. The image is applied with sobel edge detection which produces efficient results in connected components to support region identification. The edge detected image is used to perform mass estimation.

### 3.3 Mass Estimation:

At this stage, the detected edges are used to identify various regions and we identify the regions of the image and extract various regions from the edge detected image. From the regions identified, we compute the white gray mass value of the region based on the gray scale values of the pixel. The number of white and black pixels are identified and based on the values of pixels, the mass value is estimated.

Algorithm:

Input: Image \( I \),

Output: Mass Set \( \text{Ms} \).

Step1: Identify Regions \( \text{ROI} = \sum_{i=1}^{N} \text{Regions} \times \text{Connected Components} \).

Step2: for each Region from ROI

- compute Number of White pixels \( W = \sum P_i > 200 \)
- Compute number of black pixels \( B = \sum P_i < 200 \)
- compute area \( \text{Area} = \sum_{i=1}^{A} A_1 + A_2 + \ldots + A_n \)
- Compute mass \( M = \frac{W}{\text{Area}} \times B \)
- Compute average white pixel value \( \text{Aw} = \frac{\sum W_i}{N} \)

end.

Step3: stop.

### 3.4 Segmentation:

The segmentation process is performed to differentiate and group similar pixels from other pixels. In our approach the segmentation is performed based on the gray scale values of the pixels. The cancer affected cells has more gradient values than other pixels, so that we represent them in white color and
leaves other pixels with the same value what they have. The segmentation process generates number of regions and groups the similar pixels with more mass ratio to form a group.

Algorithm:

Input: image I, Mass Ms.

Output: Segmented image I.

For each region R from ROI

if MS(R).Aw > White Threshold Then
    Represent the pixel in white color
else
    Represent the pixel in block color.
end.

3.5 Lung Cancer Detection:

The cancer from the image is detected and marked based on computed region mass value. We have computed region mass value for different regions of the image and we select the most region mass value from computed set of mass values. The interest point and window size and the pixels comes into this region will be marked with different color to represent the cancer detected portion of the image.

Algorithm:

Input: Region Mass value Set MS, Segmented image I.

Output: LCD marked image Img.

step1: select most maximum mass value from MS as MMS = \( \int \text{Max}(Ms + Aw) \)

Step2: mark those pixels with different color.

Step3: stop.

4. RESULTS AND DISCUSSION

The proposed method has been implemented in Matlab and we have evaluated the proposed approach with various data sets. The proposed method has produced efficient results. The proposed region based mass estimation and segmentation for lung cancer detection has been evaluated with various data sets. The proposed method has been implemented on Matlab and tested with different 30 percent of images and for training we have used 70 percent of images of data set. The proposed method has produced efficient results and produced less time complexity also.
Figure 2: shows the gray scaled input image

Figure 3: shows the edge detected image.

Figure 4: shows the cancer detected image.
The lung cancer detection accuracy has been evaluated as follows:

\[
DA = \frac{NCC + NNN}{NCC + NNC + NNN + NCC} \tag{1}
\]

NCC – Number of classification of cancer as cancer

NNN – Number of classification of normal as normal

NNC – Number of classification of normal as cancer

NCN – Number of classification of cancer as normal.
The Figure 6 shows the false positive results produced by the proposed method according to number of training images, and it shows clearly that the proposed method has produced efficient results with more training images.

5. CONCLUSION

We proposed a naval region based mass estimation technique for image segmentation and lung cancer detection using gabor filters, where each image is converted to gray scale and applied with Gabor filter to enhance the quality of image. The enhanced image is applied with sobel edge detector to identify the regions of input image. From the extracted region of interest, we compute the gray scale mass value for each region identified. The estimated mass value is used to segment the image and based on mass value and average white pixel value of the region the lung cancer detection is performed. Finally a region with cancer affected is selected and marked using cancer detection process which is performed according to the mass estimation. The proposed method has produced efficient results and reduced the overall time, complexity and false ratio.

REFERENCES


IEEE transactions on visualization and computer graphics, vol. 17, no. 1.

