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Lung image denoising, Segmentation & Classification Using MATLAB

Kushal Suraboyana[1] Shivam Ganjoo[2] , Ritu Raj[3] ,

Prof. C . Rangaswamy[4]

[1]Department of ECE, SAIT (India)

[2]Department of ECE, SAIT (India)

[3]Department of ECE, SAIT (India)

[4]Department of ECE, SAIT (India)

ABSTRACT

A pulmonary nodule is the most common sign of lung cancer. The proposed system efficiently predicts lung tumor from Computed Tomography(CT) images through image processing techniques coupled with neural network classification as either benign or malignant. The lung CT image is denoised using non-linear total variation algorithm to remove random noise prevalent in CT images. Optimal thresholding is applied to the denoised image to segregate lung regions from surrounding anatomy. Lung nodules, regions approximately spherical regions of relatively high density found within the lung regions are segmented using region growing method. Textural and geometric features extracted from lung nodules using gray level co-occurrence matrix(GLCM) is fed as input to a back propagation neural network that classifies lung tumor as cancerous or non-cancerous. The proposed system implemented on MATLAB takes less than 3 minutes of processing time and has yielded promising results that would supplement in the diagnosis of lung cancer.

Keywords: ***Nonlinear total variation denosing, Optimal thresholding ,Region growing, Gray level co-occurrence matrix, Textural features, Back propagation network, Lung tumor prediction.***

1. INTRODUCTION

Lung cancer is the most common cause of death due to cancer for both mena nd women throughout the world. The five-year survival rate is about 15% and it has not significantly increased over the last 20 years . Early diagnosis of lung cancer can improve the effectiveness of the treatment and therefore fast accurate analysis of pulmonary nodules is of major importance.

Lung cancer results from an abnormality in the body's basic unit of life, the cell. Normally, the body maintains a system of checks and balances on cell growth so that cells divide to produce new cells only when new cells are needed. Disruption of this system of checks and balances on cell growth results in an uncontrolled division and proliferation of cells eventually forms a mass known as tumor. Tumors can be

benign or malignant. Benign tumors usually can be removed and do not spread to other parts of the body whereas malignant tumors, on the other hand , grow aggressively and spread to other sites in the body.

Medical imaging allows looking inside the body, without resoting to invasive methods. Not only more comfortable and safe for the patient, imaging also allows views of anatomy and physiology that cannot be obtained by any other means. Medical imaging plays an important role in early nodule detectin and treatment of cancer. It also guides the physician with information for efficient and effective diagnosis.

Computed Tomography(CT) is one of the best imaging technique for soft tissue imaging behind bone structures. A CT image has high spatial tissue resolution, minimizes artifacts and provides excellent visualization of anatomical features for analysis. In earlier stages, lung cancer is most commonly noticeable in CT images radiologically as a non-calcified solitary pulmonary nodule. Nodules are visible as low-contrast white, approximately spherical objects within the lung fields.

Image segmentation facilitates delineation of anatomical structures and other regions of interest. Segmentation is one of the most difficult tasks in image processing and determines the outcome of analysis and evaluation of pathogical regions. Neural networks are used widely for classification of image analysis in several biomedical systems. The aim of the proposed system is to predict lung tumor thorugh efficient segmentation and neural network classification.

2. LITERATURE SURVEY

Al-kadi and Watson(2008), in their work have discussed the potential for fractal analysis of time sequenced contrast enhanced CT images to distuingush between aggressive ad non-aggressive lung tumors. In their work, DICOM images is acquired from a CT scan was transformed to the Fractal Dimension(FD) using box counting algorithm at different scales and then FD slope and intercept the computed least square linear regression. The ROI after fractal transformation are easily identified and are selected manually. The average FD, lacunarity was computed from the ROIs. To evaluate the system, 15 patients injected with a contrast agent and a minimum of 11 time sequence CT images from each patient was considered for analysis. Based on the observation, the vascularised tumor regions exhibited strong fractal characteristics and fractal texture features was averaged ovr the tumor regions. The quantative classification showed accuracy up to 83% in differentiating between benign and malignant lung tumors and also provides additional information about likely tumor aggression.

Zhong et al.,(2008) have presented a robust joint registration and segmentation of serial lung CT images for image-guided lung cancer diagnosis and therapy. The serial image registration is done to refine longitudinal deformation using a 4D elastic image wrapping algorithm based on the Bayesian framework and was found to tolerate temporal anatomical and tissue changes. The 4D segmentation algorithm considers both spatial and temporal neighbourhoods to compute segmented images and clustering is performed to classify voxel of serial images into tissue types. The algorithm is iterated to improve the robustness and temporal stability.

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A dataset of serial lung CT images from 20 patients with a time interval of 2-3 months between scans was experimented with. The processing time was under 2.5 minutes with 2 or 3 iterations.

Serhat et al..,(2008) have developed a novel method for automated lung nodule detection in serial section CT images. They have segmented the lung regions using cellular neural networks with parameters computed using genetic algorithm to reduce the number of ROIs, search space and the computation time. The nodules were classified by convolving the 3D ROI image with the constructed 3D nodule template and a similarity measure was taken. Finally the fuzzy rule based thresholding based on maximum entropy was applied to extract the nodules. Their computer aided diagnosis(CAD) system was evaluated with 16 cases consisting of 16 nodules and 425 slices from lung image database consortium(LIDC) and high(100%) sensitivity with an acceptable number of false positives 13.375 regions per case.

Jamshid et at., (2008) have developed an efficient algorithm for segmenting various types of pulmonary nodules in thoracic CT scans using a region growing approach [5]. They have used local adaptive segmentation based on local contrast to extract foreground region which is advantageous in segregating blood vessels, adjacent tissues from nodules. In their work, a mask was created to eliminate unconnected foreground objects and for optimal seed point determination. Their algorithm is not sensitive to initial seed point selection by the user as optimum seed points are determined prior to nodule segmentation and other parameters are estimated adaptively for each nodule. To delineate the lung nodules a fuzzy connectivity map is constructed by applying the fuzzy connectivity region growing technique and on which a spherical contrast based region growing technique was applied. The halting criterion for region growing is not threshold and hence the regions grow dynamically in a spherical fashion. Their method was tested on 815 pulmonary nodules and 84% of the frrst result of the segmentation was accepted by the radiologist.

Farag et al., (2005) have introduced a template model and CAD system design for quantitative nodule detection in low dose chest CT scans [6]. The lung tissues are isolated from the input image and 3D anatomical structures are extracted to reduce search space. Since normal objects and nodules have similar gray level distribution, they have proposed 3D deformable nodule prototype using level sets that describes physical nodules irrespective of shape, size and distribution of gray levels to detect nodule candidates among all other objects. The 3D Gaussian intensity pattern in each gray scale nodule prototype ensures that the marginal gray level distribution closely approximates the empirical one for each real nodule. The parameters for the model are automatically estimated from the segmented data and no priori learning is required. The template model was able to search nodules exhaustively without any increase in processing time. Their algorithm was tested on 16 normal and 34 abnormal CT scans and achieved a detection of 93.3% and 3.34% for true positive and false positive nodules respectively. The proposed system applies optimal thresholding on 2D lung CT to segment the lung tissue and then region growing segmentation to extract the ROIs. A set of textural features are extracted from ROIs by constructing a gray level

cooccurrence matrix of the ROI. The extracted feature vectors stored in a database are used to train back propagation network that classifies whether the given diseased lung image is benign or malignant. The results were shown to an experienced radiologist and the system performance was based on his findings.

3. BLOCK DIAGRAM

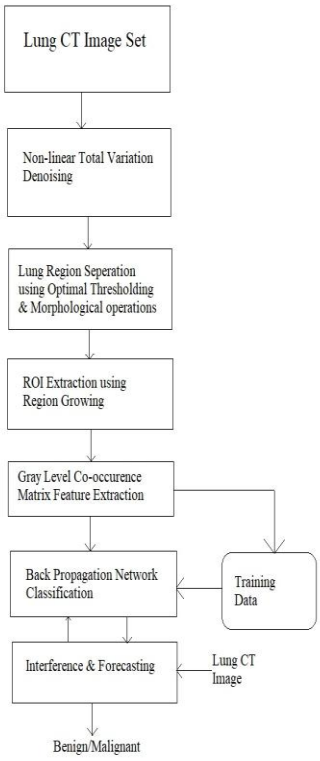

Fig 1 : Block Diagram

1. Image Denoising

CT images are found to have random noise. The random distortion makes it difficult to perform perfect image processing. The non-linear total variation based on partially differential equation algorithm proposed by Leonid et at. [7], is chosen because it effectively removes random noise present and also smoothens the image. The input to the denoising module is a 2D lung CT image in JPEG format of size 512 x 512. Let the observed intensity function Uo(x, y) denote the pixel values of a noisy image. Let u(x, y) denote the desired clean image, and n be the additive noise, is represented in (1).

$$u_0(x,y) = u(x,y) + n(x,y) \quad (1)$$

The total variation of the image is minimized subject to constraints involving the statistics of the noise. The constraints are imposed using language multipliers as in (2). The solution is obtained using gradient-projection method with time as a parameter.

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$$u_t = d/dx(u_x/\sqrt{u^2_x+u^2_y})+d/dy(u_y/\sqrt{u^2_x+u^2_y}) - \lambda(u-u_0) \quad (2)$$

As $t\rightarrow\propto$ the solution converges to a steady state, the required denoised image is obtained. The constrained optimization type of numerical algorithm is simple, accurate and relatively fast.

2. Segmentation of Lung Regions

The pre-processed lung CT consists of high intensity pixels in the body and low intensity pixels in the lung and surrounding air. The non-body pixels are the surrounding air that lies between the lungs and the dark background. The lung regions are segmented by separating the pixels corresponding to lung tissue from the pixels corresponding to the surrounding anatomy. Optimal thresholding proposed by Shiying et al. [8], is applied on the pre-processed lung image to select a segmentation threshold to segregate the body and non-body pixels through an iterative procedure

The initial threshold T^0 s average of minimum and maximum intensity in the image.

Let T^i be the segmentation threshold at step i.

To choose a new segmentation threshold, segment the image with the current threshold to separate body and non-body pixels of the image.

Let μ_b and μ_n be the gray-level of the body and non-body pixels after segmentation.

The new threshold T^{i+1} is determined using (3).

$$T^{i+1} =(\mu_b+\mu_n)/2 \quad (3)$$

Repeat steps 3-5 until there is no significant difference between threshold values in successive iterations($T^{i+1}=T^i$)

The lung image after segmentation with optimal threshold value contains non-body pixels such as the air surrounding the lungs, body and other low-density regions within the image and is removed through morphological operations as shown in Fig. 3. Background pixels are identified as non-lung pixels connected to the border. The air surrounding the body and image background is not relevant to the study, hence cleared. Noises caused by imaging operations and airways such as trachea or the bronchi may result in empty cavities. These holes are filled. Small disconnected regions if any are then discarded if the area is minimal. The lung regions are identified and extracted by replacing intensity values of pixels in the lung region with the intensity values of the denoised image. All pixels in the non-lung regions were then set to 255.

3. ROI Extraction.

Lung nodules are approximately spherical regions of relatively high density found in CT images. Lung nodule, also referred to as tumor regions, is a white mass of tissue located in the lungs. In this work, lung nodules are the desired regions of interest. Region growing is a segmentation method especially used for the delineation of small, simple structures such as tumors and lesions. The ROIs are segmented using region growing method as follows:

In lung CT images the tumor regions have a maximum intensity value of 255. A pixel is added to the regions if it satisfies the following criteria:

>> The absolute difference between the seed and any pixel is less than 50. The value of 50 is arrived after analyzing the histogram.

>> A pixel is included, if it has 8-connectivity to any one of the pixels in that region

>>If a pixel is connected to more than one region then the regions are merged.

Region growing is one of the best methods to segment tumor regions as the borders of regions found by region growing are perfectly thin and connected. The extracted ROIs are then subject to feature extraction for analysis.

4. Feature Extraction

Textural features from the spatial distribution can be used to characterize images. The extracted ROIs can be distinguished as either cancerous or not using their texture characteristics. Gray Level Co-occurrence Matrix (GLCM) is one of the most popular ways to describe the texture of an image. GLCM is defined as a matrix of relative frequencies p(i,j) calculated as how often a pixel with the intensity i occurs in a specific spatial relationship to a pixel with value j. Features such as area, convex area, equiv diameter, eccentricity, solidity, energy, contrast, correlation and homogeneity were considered for classification in the proposed work.

The features are defined as follows:

**Area*: It is a scalar value that gives the actual number of pixels in the ROI

* *Convex Area*: It is a scalar value that gives the number of pixels in convex image of the ROI which is a binary image with all pixels within the hull filled in.

* *Equiv Diameter*: It is the diameter of a circle with the same area as the ROI as defined in (4)

$$\text{equivdiameter} = (\sqrt{4*\text{Area}})/\sqrt{\pi}. \quad (4)$$

**Eccentricity*: The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. The value is between 0 and 1.

* *Solidity*: It is the proportion of the pixels in the convex hull that are also in the ROI, defined in (5).

$$\text{Solidity}=\text{Area}/\text{Convex Area} \quad (5)$$

**Energy*: It is the sum of squared elements in the GLCM as in (6) and the value ranges between 0-1.

$$\text{energy}=\Sigma p^2(i,j) \quad (6)$$

* *Contrast*: It is the measure of the intensity contrast between a pixel and its neighbour over the whole ROI as in (7) where Ng is the number of distinct gray levels.

$$\text{Contrast}=\Sigma\Sigma(i-j)^2 p(i-j) \quad (7)$$

**Correlation*: It is the measure of how a pixel is correlated to its neighbour over the ROI as in (8). Value ranges between -1 and + 1.

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$$\text{Correlation}=\Sigma\Sigma(p(i-j)-\mu_{row}\mu_{col})/\sigma_{row}\sigma_{col} \quad (8)$$

* *Homogeneity*: It is the measure of closeness of the distribution of elements in the GLCM to the GLCM of each ROI as in (9). Value ranges between 0 and 1.

5. Back Propagation Network Classification

Back propagation network(BPN) is a systematic method for training multi-layer artificial neural networks. Back propagation provides a computationally efficient method for changing the weights in a fees forward network with differentiable activation function units to learn a set of input-output examples.

The total number of nodes in the input layer is 9 representing features extracted from ROI. The number of nodes in the hidden layer is 5 was decided experimentally as the network produced good results. The output of BPN is a single value, hence one node in the output layer.

The nodes in one layer connect to the nodes in the next layer by means of directed communication links, each with an associated randomn weight. Since the BPN has one hidden layer and output layer, it results in two weight matrices, w1 connecting the input layer to the hidden layer and the w2 connecting the hidden layer to the input layer.

The network is trained using log-sigmoid activation function with a learning rate of 0.1 to evaluate the feature vectors based on the current network state. The error threshold is set as 0.1 and maximum number of epochs as 500. the output calues lie in the range 0 to 1. a threshold value of 0.5 is selected to distuinguish between cancerous and non-cancerous lung nodules. The processing tie takes by the network is less than a minute.

6. Interference and Forecasting

A lung CT image is given as input to the subsystem. The in-out image is preprocessed, lungs and then ROIs are segmented and textural features extracted. It then applies BPN classification technique to predict lung tumor as either benign or malignant.

4. RESULT

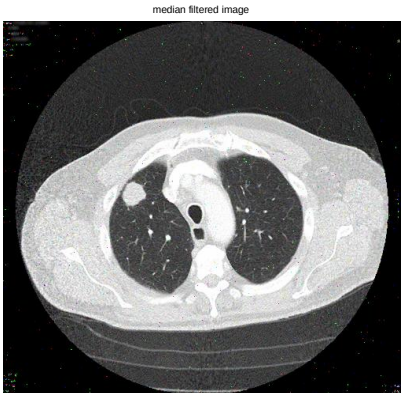

fig 2(a) : Original image

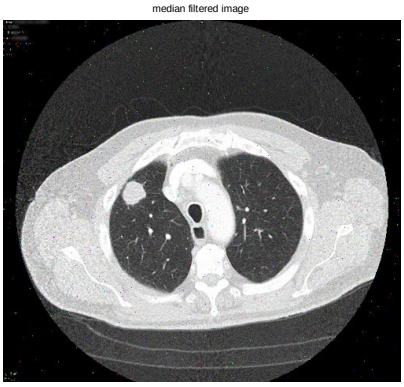

fig 2(b) : Denoised image

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the PSNR ratio for the original image is compared to the denoised image.

5. CONCLUSION

A set of textural features extracted ROIs is classified by the BPN. The system was able to predict whether the tumor was benign or malignant in nature with an accuracy of 86.3% within 3 minutes. The proposed system would be effective in assisting the physician in identifying the lung tumor as cancerous or non-cancerous.

The proposed system can be enhanced in the following ways. The accuracy of the network can be improvised by training it on a very large image set and classification based on hybrid systems. The classification can be extended to include various stages of malignant tumor and computation of growth rate.

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