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Unambiguous segmentation on computed tomography images using Bezier curve fitting algorithm

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Abstract: World-wide increase in diseases has led to accurate analysis and computer-aided disease diagnostics for better medication and speedy recovery. This work aims at computerizing the analysis section, involves passing the available images and its database in basic three stages like enhancement, segmentation and feature Extraction stage to achieve more quality and accuracy in detection. Image segmentation is the process of partitioning a digital image into multiple super-pixels. The proposed work suggests a technique for segmentation of image from Computed Tomography. This work uses Bezier curve fitting algorithm for segmenting the CT image. Segmentation algorithm used in this work helps in segmenting the pathological bearing regions along the edges of even, if the part is asymmetric.

I. INTRODUCTION

The discoveries or seminal physical phenomena such as X-rays, ultrasound, radioactivity, arid magnetic resonance, and the development of imaging instruments that harness them have provided some of the most effective diagnostic tools in medicine. The medical imaging community can probe into the structure, function and pathology of the human body with a diversity of imaging systems. These systems are also used for planning treatment and surgery, as well as for imaging in biology. Data sets in Iwo. Three, or more dimensions convey increasingly vast and detailed information for clinical or research applications. This has to be interpreted in a timely and accurate manner to do well to health care. One of them is X-ray computed tomography, also computed tomography (CT scan) or computed axial tomography (CAT scan), which is a medical imaging procedure that utilizes computer-processed X-rays to produce tomographic images or 'slices' of specific areas of the body. In this paper we have examined the human lungs, the essential respiration organ for human beings. This paper presents concepts of digital techniques, processing and analyzing medical images after they have been generated. It is organized into 3 process that correspond to the fundamental classes of algorithms of (1) Image Segmentation, where the interested region is tracked by Bezier algorithm. (2) Feature Extraction, which adds the flavor in identifying the presence of a certain type of feature or object in an image and (3) Classification.

The goal of image segmentation is to change the depiction of an image into somewhat that is more meaningful and easier to analyze. This is a platform often a stage where a significant commitment is made during automated analysis by delineating structures which need attention and discriminating them from background tissue. This separation, which is generally effortless and swift for the human visual system, could be a challenge in algorithm development. In many cases the segmentation approach dictates the upshot or the entire analysis, since measurements and other processing steps depend on segmented regions. Segmentation algorithms operate on the intensity or texture variations of the image using techniques that include thresholding, enhancement, enhancement and segmentation.

The result of image segmentation is the set of segments that collectively cover the image, or a set of contours extracted from the image. Every pixel in an area is alike with some of the characteristic or computed property, such as color, intensity, or texture. Adjacent regions are ominously different. When stack of images are applied, typically in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation.

Feature extraction is a process of transforming the input data into the set of features. The input data to classification algorithm is too large for processing and it is suspected to be extremely redundant, then the input data will be transformed into a reduced representation set of features (also named features vector). Feature extraction can be achieved by studying the statistic variations of certain regions and their backgrounds to locate unusual activities. Once an interesting

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feature has been detected, the representation of this feature will be used to compare with all possible features known to the processor. A statistical classifier produces a feature type that has the closest similarity (or maximum likelihood) to the testing feature. Data collection and analysis (or the training processes) are performed here at the classifier before any classification. *Classification* is process of Machine learning based detection and recognition of lung diseases can provide clues to identify and treat the diseases in its early stages.

The rest of the article is organized as follows. In Section II is a literature survey. System architecture is discussed in Section III. Section IV presents the experimental results. Conclusions are discussed in Section V.

II. LITERATURE SURVEY

Elizabeth et al [2012] proposed a segmentation approach for improving diagnostic accuracy. This approach involves the conventional optimal thresholding technique and operations based on convex edge and centroid properties of the lung region. Manual segmentation of lung parenchyma becomes difficult with an enormous volume of images. The goal of this work is to present an automated approach to segmentation of lung parenchyma from the rest of the chest CT image. The segmentation technique proposed in this article can be used to pre-process lung images given to a computer aided diagnosis system for diagnosis of lung disorders. This improves the diagnostic performance of the system. Pathology bearing regions along the edges of the lungs are not segmented if they are asymmetric and vary in the convex area.

Most of the segmentation algorithms for lung CTs discussed in the literature are pixel-based methods. Heubergeret al. [2005] suggest that as the lung parenchyma has a very low density, it is composed of low-intensity pixels in the CT scan. This property is exploited to separate the two lungs from the surrounding tissue. Generally, the image is thresholded, either at a fixed value or based on a computed threshold. Heuberger et al. [2005] have proposed a technique for lung CT segmentation forimage retrieval using the Insight Toolkit (ITK). Their lung segmentation algorithm follows five steps: thresholding, removal of surrounding air, cleaning, rolling ball operation, and left and right lung separation. The approach works well when the PBR is internally placed. The algorithm is unable to track the lung border if the PBR is peripherally placed and larger than the size the rolling ball operator can handle. In some cases, wherein a lung lobe touches the border, that lobe is eliminated along with the background. Their goal had been to present an algorithm that does not need manual intervention. Silva et al. [2002] have described an automatic segmentation method for the pulmonary parenchyma. The method is based on a combination of traditional techniques such as segmentation using global threshold, morphological opening and closing operations, border detection using Sobel's filter, thinning, representation of pulmonary structures using chain code, classification of the structures' areas, and reconstruction of the pulmonary parenchyma using a rolling-ball algorithm. Their algorithm also relies on a rolling ball operator for rebuilding the lung border and hence is unable to track the lung border if the PBR is peripherally placed and larger than the size the rolling ball operator can handle. They tested the method with 150 CT images and found that for 135 images the results matched the expectation and for the other 15 the results were incorrect.

Antonelli et al. [2005a] presented a method for automated identification of the pulmonary parenchyma. The method is based on a combination of either traditional or purposely-developed image processing techniques, such as threshold-based segmentation, morphological opening and closing operations, border detection, border thinning border reconstruction, and region filling. In order to reconstruct the border for each pair of border points, they calculate two distances; the Euclidean distance and the minimum distance in pixels between the two points. They then compute the ratio of minimum distance to Euclidean distance: if it is greater than a given threshold the two points are considered candidates for a possible reconstruction. For all candidate pairs a further condition is evaluated before establishing whether the reconstruction has to be done: they verify whether the segment connecting the two points is not internal to the lung. If this condition is satisfied, then the border between the pair of points is rebuilt. This technique also works fine when the size of the peripherally placed nodule is small. Antonelli et al. [2005b] described an automated system for detection of pulmonary nodules in CT images of lungs. In their work they used the segmentation technique proposed by Antonelli et al. [2005a] for extraction of lung parenchyma as a preprocessing step. They worked on scans consisting of a sequence of about 300 slices stored in DICOM format. They showed that small juxta-pleura nodules could be identified by their system as a consequence of the segmentation algorithm used. Pu et al. [2008] presented a lung segmentation algorithm called adaptive border marching (ABM). Smoothes the lung border in a geometric way and can be used to reliably include juxta-pleural nodules while minimizing over segmentation of adjacent regions such as the abdomen and media stinum. They have compared their technique with the rolling ball approach. Their technique

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performs better but tends to include a part of the non lung tissue in the segmented lung parenchyma. Elizabeth et al. [2009] used an optimal thresholding method for segmentation of lung tissue in a CAD system to detect bronchiect as is in CT images of the chest. They used the Mahalanobis distance measure and Probabilistic Neural Network (PNN) for performing diagnosis, and achieved an accuracy of 96.49% using the mahalanobis similarity measure and 98.19% using the probabilistic neural network. From the literature it can be observed that optimal thresholding is suitable in case where PBR does not exist in the periphery of the lung parenchyma and a rolling ball operator can be used when there are small juxta-pleural nodules. Our work is different from that discussed in the literature in that it reconstructs the edge by using the convex area property of the lung, in addition to the grayscale value. The technique reconstructs the edge of the lung in the presence of peripheral nodules of moderate size against the rolling ball mechanism, which reconstructs the edge in the presence of small peripheral nodules. [5] proposed a system which uses intermediate features of maximum overlap wavelet transform (IMOWT) as a pre-processing step. The coefficients derived from IMOWT are subjected to 2D histogram Grouping. This method is simple, fast and unsupervised. 2D histograms are used to obtain Grouping of color image. This Grouping output gives three segmentation maps which are fused together to get the final segmented output. This method produces good segmentation results when compared to the direct application of 2D Histogram Grouping. IMOWT is the efficient transform in which a set of wavelet features of the same size of various levels of resolutions and different local window sizes for different levels are used. IMOWT is efficient because of its time effectiveness, flexibility and translation invariance which are useful for good segmentation results.

III. PROPOSED WORK

In our proposed work Bezier curve fitting algorithm is used to segment the suspected pathological bearing regions along the edges of the lungs even if they are asymmetric.

A. System architecture

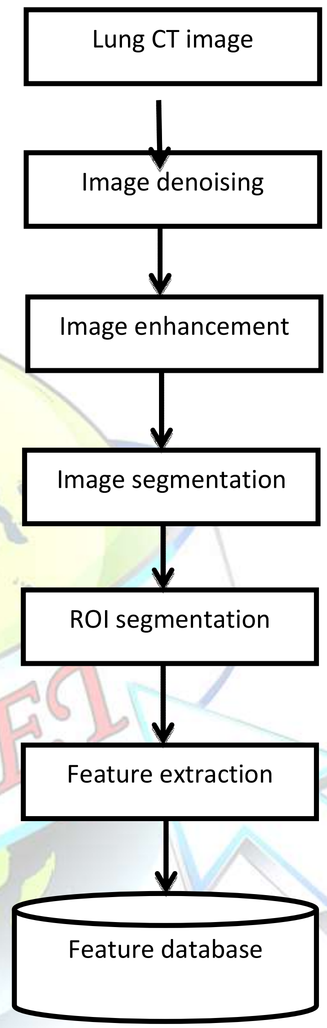

Fig.1 shows the system architecture of this work.

B. Image denoising

The aim of pre-processing is to improve image data so that it suppresses undesired distortions and/or enhances image features that are relevant for further processing such as enhance the visual appearance of images and improve the manipulation of datasets.

The input to this subsystem is a JPEG image of a chest CT scan of size 512 × 512 pixels. The aim of pre-processing is to improve CT image data so that it suppresses undesired distortions and enhances image features that are relevant for further processing such as enhance the visual appearance of

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images and improve the manipulation of data sets. 2-D adaptive noise-removal filtering is used to remove the Gaussian noise from the CT image. A piecewise Wiener filter is used for eliminating Gaussian white noise present in the CT lung image as defined by Equation 1.

$$s(x_1, x_2) = \alpha + (\sigma^2 – v^2 / \sigma^2) (b (x_1, x_2) - \alpha) \quad (1)$$

Where v2 is the noise variance, and μ and σ2 are the estimates of the local mean and variance around each pixel. The denoised CT chest image B obtained as the output of the Weiner filter is deconvolved with a point spread function (PSF) using the Wiener filter algorithm to get the deblurred image.

C. ROI *extraction*

Architecture for object-based region of interest detection is proposed. ROI is defined as regions containing user defined objects of interest, and an efficient algorithm is developed for the detection of such region. The main goal of this step is to determine the (ROI) region of interests in lung images. The ROIs for our system are suspected defect tissues. Pixel based segmentation is used to extract the suspected defect tissues from the entire lung region. The regions other than these tissues are removed by morphological operations. Many applications in image processing require the variable assignment of resources to different image regions. In general images can be displayed with spatially variable resolution to enable faster browsing or manipulation, image regions can be subject to variable degrees of error correction to achieve an optimum trade-off between transmission reliability and efficiency, or images can be encoded with spatially varying bit rates so as to guarantee higher fidelity in the regions that are deemed more importance to their viewers.

D. Image segmentation

Image segmentation is the process of partitioning a digital image into multiple super-pixels. The goal of this work is to present an automated approach to segmentation of lung parenchyma from the rest of the chest CT image.

Edge reconstruction algorithm:
INPUT: lung CT image (Affected and Normal slice)
OUTPUT: Reconstructed Edge

i. Read Lung CT image img_aff(m, n) and img_nor (i, j)

ii. Set the value of L1 such that it splits the lungs image, img_aff(m,n) into two portions.
   a. Set L1= 0.5*n; L2= L1+1;
   b. Left_lung = img_aff (m, L1);
   c. Right_lung = img_aff (m, L2);

iii. Find the threshold for the left and right image
   a. Threshold (Left_lung);
   b. Threshold (Right_lung);

iv. Count the total number of black pixels in the left and right image and compare it to find which part has less black pixels. This step helps in determining which part of the lung is mostly affected.

```
if(bwcount(Left_lung) < bwcount (right_lung) )
affected=Left
else
affected=right
```

v. Extract the extreme left black pixel, extreme rightmost pixel, topmost pixel and bottom most pixels in the affected lung image and retrieve co-ordinates of those points (p_0) from the image img_nor (i,j).

vi. Read the set of points (p_0), which is a 2D array matrix i.e., $p_0 = p_1, p_2, p_3, \ldots, p_n$

vii. Identify segnum = number of points-1

Case 1:
   if number of points <=1
   return error.

Case 2:
   if number of points =2 i.e., only straight line is possible.
   if (segnum==1)
   $3p_1 = 2p_0 + p_3$

	Constrast	Correlation	Cluster shade	Homogeneity
ROI 1	0.003599	0.709120379	2.138470962	0.003765522
ROI 2	0.002969	0.801415891	3.422464399	0.00359928
ROI 3	0.005624	0.708566621	3.449402369	0.005396342
ROI 4	0.012321	0.904321838	32.59304951	0.02204818
ROI 5	0.010568	0.846916614	14.18738075	0.014612749
ROI 6	0.005426	0.814401339	5.872877483	0.007038947
ROI 7	0.004001	0.668113207	2.274498353	0.003228287

   $p_2 = 2p_1 - p_0$

Case 3:

if number of points>=3 i.e., curve is possible.
To find start point
$p_{start} = 0.5 * (p_0 + p_1)$
To find end point
$p_{end} = 0.5 * (p_2 + p_3)$

viii. Impose the points (p_0) into the image img_aff (m, n). A Bezier curve is plotted between the points p_{start} and p_{end} using plot function.

ix. The CT image of the existing segmentation work (fig.2) is probable of not detecting any flaw in the lung, though it exists. Image segmentation through the proposed work (fig.3) is sure of detecting all the available flaws as this curve fitting algorithm extrapolates its range of analysis and thus it is unambiguous.

Fig.2 Segmentation – Existing work

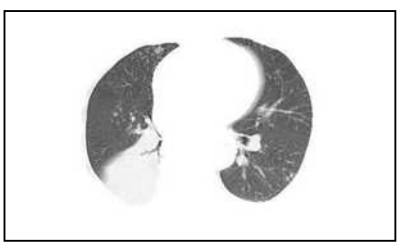

Fig.3 Segmentation – proposed work

E. Feature extraction

A feature is a significant piece of information extracted from an image which provides more detailed understanding of the image**. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.** Features such as Area, Convex area, Equiv Diameter, Eccentricity, Solidity, Energy, Contrast, Correlation, Homogeneity, Mean, Standard deviation, Smoothness, Third Moment, Uniformity Entropy is taken into account [18] as shown in the fig 4.

Fig.4- snapshot of feature extraction

IV. RESULTS

The database contains 81 nodules that are identified in40 patient scan sets, with slice thicknesses ranging from0.5 to 2.0 mm and X-ray tube currents ranging from 80 to300 mA. The specificity, accuracy, precision and recall of the system were computed as defined by Equations (1), (2), (3), and (4).

Specificity = TN/ TN + FP (1)
Accuracy = TP + TN /TP + FP + TN + FN (2)
Precision = TP /TP + FP (3)
Recall = TP /TP + FN, (4)

where TP, True Positives are regions detected positive; FP, False Positive are regions detected negative; FN, false negatives are regions missed by our system and classified as positive and TN, true negatives are regions missed by our system and classified as negative .

table 1. shows the values of all the performance measures. The values of TP, FP, FN, and TN were determined based on the feedback.

Performance measure	**Existing work**	**Proposed work**
Specificity	96.5%	97%
Accuracy	94%	98%
Precision	94.3%	96.05%
Recall	95%	98.03%

Table 1-Performance measure table

V. SOCIAL CONTRIBUTION

Lung cancer is one of the most deadliest disease. In the common CT scanned images of the chests of patients with lung disorders, if the PBR lies in the periphery of the lung parenchyma, it may not be detected by most of the existing systems and hence the diagnostic result given by the system would turn out to be negative. But, the proposed segmentation approach includes the peripheral PBRs that are excluded by the existing systems. Thereby reducing the FN rate; hence, improving the diagnostic accuracy and reducing the mortality rate of patients with lung disorders

V. CONCLUSION

Herewith, the proposed work, the unambiguous segmentation of computed tomography images could be successfully implemented in real time. Our approach definitely increases the diagnostics accuracy.The conclusion is the impact made on information quality given by the system. This work increases the True Positive and decreases the False Positive and False Negative, thereby increasing the diagnostic accuracy of the existing system.

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