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Gradient Active Contour Driven Lung Segmentation and Lung Nodule Detection System

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Abstract: *In this work, we propose novel iterative bounded active contour model initialized by gradient of boundaries to explore uneven lung region from Chest Radiography (CXR) images. This work focused on a unified image transformation framework to exploit the clinically relevant lung regions and retains potentially useful information for texture analyzes and feature extraction and selection to achieve discrimination based on the feature sub set. Moreover this work also focused on availability of gradient information at the lung boundaries active contour model is derived. Finally novel morphological and spatial feature attribues are extracted from ROI segmented lung images for auto classification of CT images. And then optimal sets are evaluated based on the variance measure of the feature values. Experimental results proved that proposed system has brought about a remarkable performance in lung CT image classification. The use of performance and consistency measures has ensured the validity of the experiments. Finally lung nodules detection and multi class classifications are performed with appropriate discrimination measure among normal and abnormal classes using Euclidean distance of hyper planes in SVM classifier. The proposed method is advantageous to early diagnostic process of lung abnormalities and disease. Finally, the performance metrics of proposed feature subsets is compared with state-of-the-art methods and verified using benchmark real-world databases. It is proved that proposed model outperforms competing feature selection methods in terms of accuracy and confusion matrix measures.*

Keywords: *ROI Lung Segmentation, PCA transform, CAD system, CT image sets, GLCM, ACM etc.*

I. Introduction

The recent advancement in image processing methodologies has led to increase the demands over early diagnosis of diseases in scan based biomedical CAD system [1-2]. In general CAD system consists of following stages: Pre-processing, ROI segmentation, transformation or classification, feature extraction, attribute selection and finally machine learning based auto classification. Compared to all other biomedical imaging (CXR, MRI, X-ray etc) computed tomography (CT) is the most sensitive and complex model for detecting cancerous lung nodules [3]. It is also proved that early stage detection has maximum survival rate and CT screening is considered prominently for clinical stage I lung

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cancer which can be curable by surgery since some of the slow growing adenocarcinomas were explore only on CT images. Regardless of the stage of lung nodule growth and methodologies used for receiving CT screening is always in nature. Therefore, devising an efficient framework for cancerous nodule detection system based on unified single compound feature set and classification method is a challenge. Many computationally rigorous methods are investigated and failed to perform consistently over various datasets [4]. Feature attributes are not able explore narrowly the abnormalities and it has been emerging steadily every day, alongside a corresponding increase in the dimension set that capture the potential metrics. In contour modelling morphological characteristics related gradient information's widely used to isolate the lung region and to accommodate uneven boundary conditions and inhomogeneity lung region ACM constitutes of accurate contour modelling is used [5].

In recent days higher-level interpretation has opened up research opportunities to monitor image statistics and its sensitiveness to the image non linear modalities [6]. Aggregated spatial information for ROI segmentation can be modelled using features like edges, colors and contours. Though Image segmentation can be modelled using feature attributes, it is the challenging task in many vision application and image processing methodologies such as medical image analysis and classification. According to the investigations made in several research works, the region of interest selection is directly related to the statistical information in the given image set [7-8]

On the other side, Image segmentation is regarded as a major problem in the literature on the subject. It is essential for any automated CAD to overcome the challenges that comes with ROI segmentation of lungs from any CT image sets [9]. Though several advanced methodologies are emerged in medical image systems still it is not even possible to accurately select lung regions which can finitely explore the disease type and severity level since the characteristics of CT images [10] and morphological explorations and difficult to examine [11]. Consequently, this section reviews the previous methods described in the literature to deal with accurate segmentation of lung images in various datasets. Automatic segmentation of lung region from CT images is a difficult task to accomplish due to following image non linearity's:

- Intensity in-homogeneity.
- Uneven boundary conditions.
- Image artifacts.

The Lung Segmentation in CT images can be done by using three methods i) Rule Based ii) Pixel Based and iii) Deformable based. In this research Novel segmentation method is proposed by fusing Active Contour Model, a deformable based approach with deep learning algorithm method to improve the accuracy of Segmentation.

Gradient Active contours are an effective edge-based method for segmenting the region of interest. In [12] considers both the gradient strength and gradient direction of the image to minimize the energy function. In [13] developed Curvature Gradient Vector Flow method to increase the item of curvature, and find the diffused edge information. In [14] multidirectional model provides a better ROI segmentation and mitigates the directional related problems over edge candidates with different directions. Curvature Gradient model has obvious advantages over conventional Gradient model like lesser number of iteration and the convergence accuracy rate. .

In this paper, intend to explore the texture information's and morphological details to analyze the input lung image with following advantages.

1) Threshold bounded texture classification model is used to exploring the spatial details from input CT lung images.

2) Potentially useful feature subsets are retained while removing all sorts of redundant features using appropriate feature transform.

4) Accurate template based feature sub set matching can significantly improve the detection rate.

In addition, to mitigate the influence of redundant feature attributes and correlated values appropriate feature selection model is incorporated in this framework as a post processing unit which can reduce storage space as well as computational time during auto classification.

II. ACTIVE CONTOUR MODEL

Active contour model always initialized with the curve evaluation function which is derived from the surface of the image and controlled by some by stopping function. During integration all the evaluated curve functions are directly coupled with the energy function. For evaluating the curve function the level set method is used which can control the motion of the curve with mean curvature.

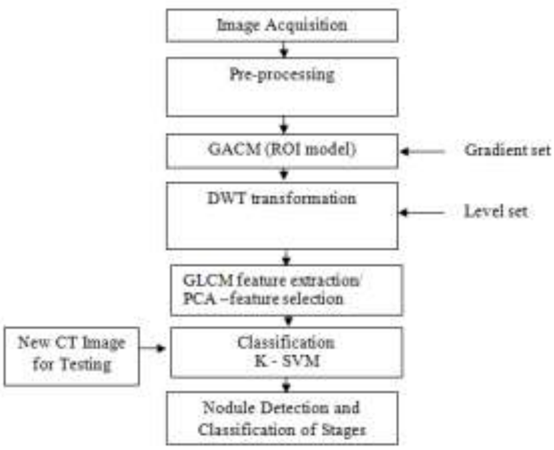

Figure.1 Proposed auto classification models

2.1 Gradient computation

The motivation for the ACM technique is that the gradient details of input CT image is used to model the ROI segmentation. The gradient values of input lung images are finitely explore the boundary regions using second order derivatives and this normalized boundary information's are used to formulate level set over all deformable contours. During the evolution level set fixed coordinate system is used for curve evaluation which is not parameterized with any threshold values as shown in Figure 1. After modelling the contours in the CT images iteration is applied with predefined threshold value in-order to explore the texture details of lung region.

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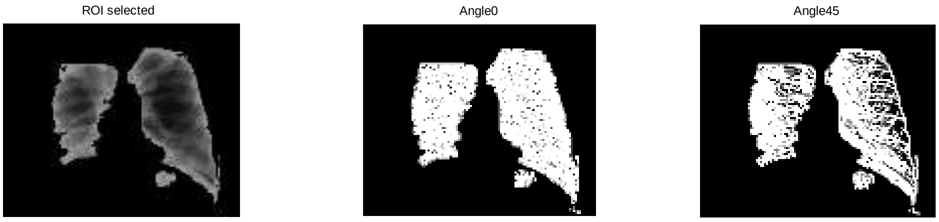
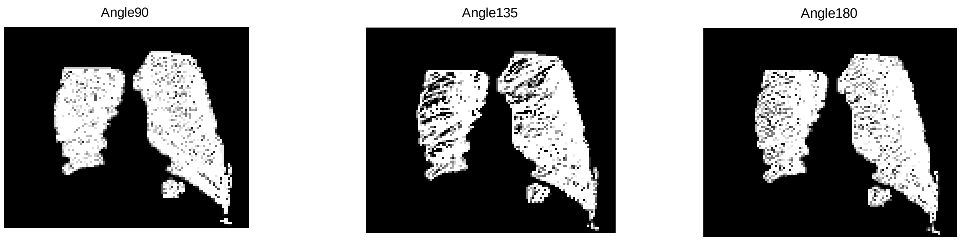
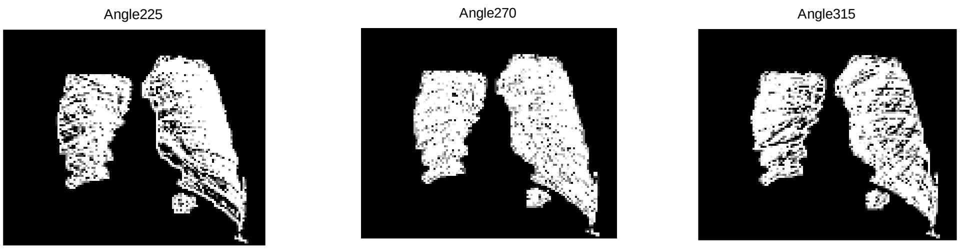
Finally, discriminate saliency is adopted to resolve problems by simply updating the models used to discriminate between the lung regions and background regions. The results from the gradient are combined by taking the maximum value from each parameter measure at each pixel as shown in Figure 2. The segmented object of interest is retained all of its morphological characteristics from CT image.



(a) input ROI region (b) Angle 0 (c) Angle 45



(d) Angle 90 (e) Angle 135 (f) Angle 180



(g) Angle 225 (h) Angle 270 (i) Angle 315

Figure. 2 Texture segmentation results

III. Feature extraction and selection

Feature extraction is used to generate some numerical values from ROI segmented image in order to obtain better discrimination among different classes of object of interest. Feature extraction is used for the compact representation (numerical data) of the invariant attributes of the lung object, and establishes the information obtained

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about the segmented lung region from CT image. The object features such as texture and shape are considered domain-specific features extracted from the spatial regions of the detected lung object. Gray-level pixel orientations are investigated for spatial domain characterises and its relationships. Here both Geometry features and spatial features are presented and feature subset reduction is carried out prior to the auto classification process.

3.1 Directive texture classification

In CAD system, texture features are used to develop diagnostic rules for the lung cancer nodule detection. To improve the performance of the conventional binary texture pattern orientation driven multi level texture classification is carrying out, based on the disparity calculation. Here, the binary texture pattern is established by comparing the magnitude value of the centre pixel with all its neighbourhood pixels as shown in Figure 4. The reported performance results of the nodule detection system are good, and competitive in terms of texture modules.

3.2 Feature attributes

The GLCM based feature extraction exploit the spatial details of ROI lung region in addition to the structural, spectral and statistical values during feature attribute generation process. Among various statistical approaches followed for spatial description GLCM with orientation angles are provides accurate texture exploration with invariant properties. Here irrespective to the angle of projection and scale variations GLCM gives better discrimination over normal and abnormal lung regions as shown in Figure 3.

The texture feature is considered for abnormal detection from ROI region for the following reasons:

- The potentially useful feature sets are extracted from different angle of coordinates to accommodate invariance level over angle of appearance.
- Highly consistent with lung CT image sets with different resolution and image dynamics.
- A SVM classifier is trained with most appropriate feature subsets.

```
BAND 1 GLCM values
    Autocorrelation: 4.969232209737828e+001
           Contrast: 3.824656679151061e+000
        Correlation: 7.420416773279174e-001
       Correlation1: 7.420416773279183e-001
         Prominence: 2.464785884760176e+003
              Shade: -2.045466208479590e+002
      Dissimilarity: 6.063670411985017e-001
             Energy: 5.669474720270075e-001
            Entropy: 1.031920896943097e+000
        Homogeneity: 9.081748632661555e-001
       Homogeneity1: 8.970831402351562e-001
        probability: 7.371410736579276e-001
           Variance: 5.141400916091214e+001
         sumaverage: 1.329531835205992e+001
        sumvariance: 1.784590875975981e+002
         sumentropy: 9.409412891904527e-001
       Diffvariance: 3.824656679151062e+000
        Diffentropy: 5.210599786045436e-001
```

Figure.3 GLCM features

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3.3 Optimal Feature Selection

Here Feature selection approaches help to reduce the size of template without causing severe degradation in performance metrics. Variance measure based PCA transform is used to retain potentially useful texture feature vectors based on redundant and discriminations. Finally dimensionality reduction is formulated to generate the best possible subsets ' features from an extracted feature set F. The proposed prominent subset selection algorithm includes following process: consistency based feature normalization to reduce the intra class variance problems associate with multi modal lung CT images, correlation driven subset reduction to mitigate interclass similarity problems.

3.3.1 Prominent feature normalization

Here consistency measures are used to evaluate the variations of GLCM features which are extracted from different directional to narrow down the sensitiveness to the illumination and scale variations. In addition to this distance identical GLCM values are also need to be removed through normalize vector orientation measure in four different coordinates as shown Figure 4. The first level subsets are formed, based on consistency factor over all four wavelet decomposed sub bands. Here most relevant features to the subject classes are selected. The total number of features filtered in the first level is 12 from 72 features extracted. The final feature subset values of each individual classes having prominent discrimination and avoids confusion metrics during classification.

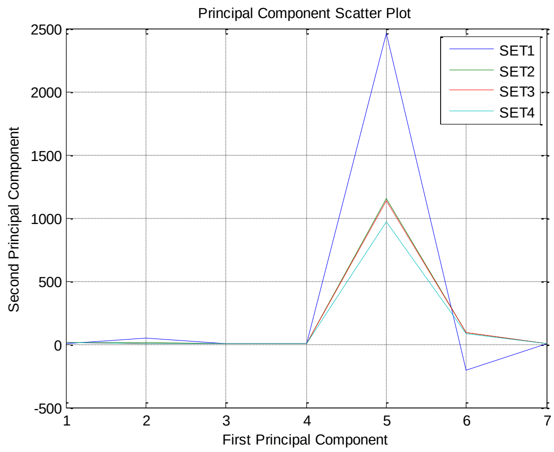

Figure 4. Consistent GLCM features

3.3.2 Finite subset selection

In our proposed approach, the SVM classifier is used for similarity matching driven auto classification and outperformed its counterpart model as shown in table 1. Keeping likelihood measures in mind, priorities are assigned to a feature with a larger variance for given CT image. The implication is that abnormal lungs region should be clearly discriminated, one from another, with these significant selected features. The features stay consistent in dealing with all types of problems that occur over various CT image datasets and scale changes as shown in Figure 5.

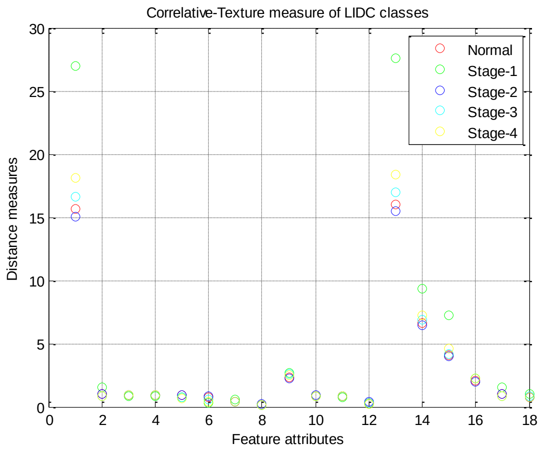

Figure 5. Correlated GLCM features

Table 1. Segmentation performance over CXR images

ROI model used	Accuracy-LIDC data set	Sensitivity - LIDC data set
GLCM-SHAPE+SVM Model [15]	**94.1**	**91.3**
proposed model	**95.3**	**92.17**

IV. Results and Discussion

In [16] classified lung nodules using statistical parameters like mean, standard deviation, skewness, kurtosis, fifth central moment and sixth central moment with feed forward back propagation ANN network. This system achieves the maximum classification accuracy 93.3%. It is outperformed by proposed classification model with improved accuracy rate of 96.1% due to the incorporation of geometric and texture details with statistical feature sub sets as shown in table 2.

Table 2 Performance measures of proposed Gradient based CAD system

Classifier used	Segmentation model used	Database	Accuracy
ANN [16].	**Morphological operation**	**LIDC**	**93.3**
		-	**-**
proposed model	**GACM model**	**LIDC**	**96.1**
		ELCAP	**94.5**

The performance efficiency proposed feature subset selection is validated by evaluating classification measures of various stages of lung cancers from public benchmark LIDC image data sets with associated confusion matrices as shown in Figure 6.

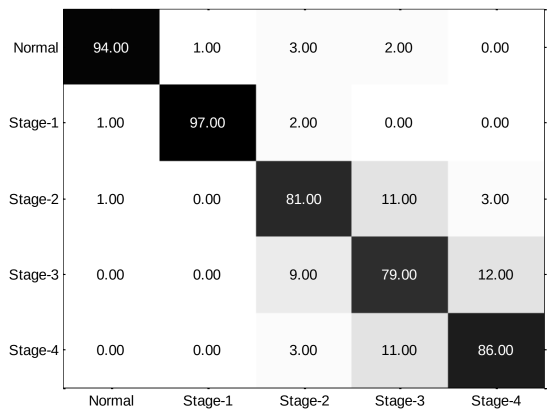

Figure .6 confusion matrix plots

V. Conclusions

This research advances a state-of-the-art lung nodule detection and auto classification system from CT lung image sets in cooperating ROI segmentation, image transformation, texture classification feature extraction and selection. This lung nodule detection was implemented with proposed framework for appropriate lung segmentation from different CT image set with various boundary condition and scale changes. This system also fulfilled the need for a semantic gap reduction of features for abnormality detection in lung images. The experimental results also proved that proposed hybrid gradient model outperforms all other state-of-the-art methods in lung image classification.

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