Lung Tumor Detection and Diagnosis in CT scan Images

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Abstract— **In recent years, the image processing mechanisms are widely used in medical image diagnosis, especially in detection of various tumors. In this paper, we propose a level set-active contour model with minimizer function for lung tumor diagnosis and segmentation. Kernel based non-local neighborhood denoising function is used to get noise free image. Second order histogram based feature extraction is accomplished for classifying the images under normal and abnormal classes. Following tumor detection, exact segmentation of the tumor is effected by level set-active contour modeling with minimized gradient. Experiments demonstrated that our methodology could segment the lung field with pathology of variant forms more precisely.**

I. Introduction

The excessively high prevalence of lung cancer has encouraged attempts for earlier detection, which is more substantial in clinical practice. The morality rate of lung tumor is the highest among all other types of tumor. Nevertheless, the endurance rate for the cancer patient can be increased by diagnosing the occurrence in earlier stages. With that concern, we adduce a mechanism for diagnosis and segmentation of lung cancer. The fundamental step of this proposal is to denoise the lung image obtained from CT image to acquire impeccable results. The ultimate aim of this work is to frame a segmentation algorithm to sever tumor using level set and active contour modeling techniques. Active contour model is also called as snake model since the progression of contour bear a resemblance to snake crawling. The model is widely used in many applications including, shape modeling, segmentation, stereo matching and object tracking. Active contour model is able to find the accurate boundary of the tumor, whose energy depends on its spatial positioning and shape changes. The idea of our proposal is to minimize the integral measure, which represents total contour energy using level set equations. Along with active contour modeling, level set equations are incorporated for the accession of segment uniformity criterion defined over the given classification. An approach called Snake Driven Particle Swarm Optimization (SDPSO) is given in [1]. The paper specified two categories of snake model representations namely, parametric active contour model and geometric active contour model, combined that with particle navigation scheme from PSO in order to surpass the limitations of active contour model. In our proposed methodology, active contour modeling is combined with level set algorithm to amend the performance. The segmentation algorithm is derived to detect the tumor, whose boundaries are not necessarily defined by gradients. As is well known, segmentation is an important phase before surgery planning. The proposal in [10] described two stages for segmentation. The first stage tumor segmentation was obtained by thresholding and when you open morphological operations, whereas the second stage refined rough segmentation using fuzzy clustering and geometric deformable model (GDM). The model could be further enhanced with the implication of average healthy tissue intensity values. Segmentation mechanism proposed with the incorporation of region-based active contour implementation in [12], which avoids delineation leakage while analyzing PET (Positron Emission Tomography)-CT images.

An algorithm for Lung nodule segmentation using active contour modeling was framed in [13]. The steps involved in the foresaid algorithm are, 1.Segmentation of lung area by active contour model, 2. Region of Interest (ROI) detection using stochastic 2D features, 3.Detection of nodules using anatomical 3D features and 4.Accurate contour extraction of nodules. There was no solution mentioned here for noisy CT images.In this paper, we present a Level set-active contour based tumor segmentation algorithm. Initially, the noisy CT image is denoised by kernel based non-local neighborhood denoising method, which follows quality metric analysis of different denoising kernel functions. The noise-free image is given for further feature extraction process that accounts several peculiar characteristics of lung image includes contrast, correlation, etc. The classification of lung image is made by the trained neural network based on Bayes Classification to categorize the image under normal and abnormal stages. Following that, segmentation of tumor is done by level set-active contour model with minimized energy. This approach outperforms the snake model, severs appropriate tumor and improves the clinical usefulness in cancer diagnosis. The rest of this paper is organized as follows. Related works are reviewed in sections 2. Section 3 describes the proposed Level set-active contour based lung tumor segmentation in detail. Experimental results are discussed in section 4. Finally, section 5 concludes this paper.

II. Literature Survey

Shinji Yamamoto *et al*. [19] developed a mobile-type X-ray CT, used for initial mass screening in lung cancer detection process. Quoit filtering method was incorporated in this paper

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to detect the cancer regions automatically in CT cross sections of lung areas. The accuracy rate of diagnosis results obtained by this method could be improved more in further experimentations. P.J.A. Robinson described the procedure for imaging liver metastases and illustrated some limitations and future prospectus over that. The paper construed about clinical examination functionalities, sensitivity status, resolution of imaging methods, optimization methods of current imaging techniques and methods for earlier detection of micrometastases. Description of liver metastases and detection methodologies using CT images were given in [16]. Michael Kass *et al*. [9] explained about the active contour models. The basic snake behaviors prescribed in this paper includes energy minimization and the controlled continuity under the influence of image forces. Perhaps, the image forces include line functional, edge functional, scale space and terminate functionalities. In [11], a new method for active contours based on curve evolution and level set formulations was developed. The boundaries were not necessarily defined by image gradient regarding this methodology. The paper did not compose any description over noisy images. There was a comparative analysis made between magnetic resonance imaging (MRI) and PET images in detection of liver metastases in [2]. The statistical analysis with parameters such as sensitivity, prediction rate and accuracy afforded vast information for clinical practice in cancer diagnosis.Bayesian classification is an immense classification methodology, which we use in our proposal. The naïve bayes classifier has been given in [5] demonstrated the classification formulations using probabilistic measurements for acquiring efficacious classification results . Analysis about metastatic diseases using CT images was given in [6]. Advancements in imaging technology had improved the ability to detect, categorize and segment cancer cells.The paper [6] presented supervision-based thresholding approach that enclosed threshold selection within the frequency range of background image. Supervision technique was adopted to determine the range of Region of Interest (ROI) variation proportional to the background. The approach could be employed in wide variety of medical image segmentation. Multistage 3-D medical image segmentation methodology and validation criteria were demonstrated in [4]. For validation, a novel radial distance-based validation method was proposed. Still more, the segmentation results could be precise while improving the methodologies with advanced techniques. On following the former, authors of [8] described the CT image segmentation using anatomical constraints. For incorporating that they framed a new segmentation cost function based on Bayesian framework. They engaged in investigating substitution method for histogram in intensity cost function determination.
Jun Lai and Ming Ye worked on active contour based lung field segmentation in [14]. The algorithm comprised preprocessing and segmentation stages with lung area profile. The segmentation results had been significantly improved by active contour using shape energy control mechanism. Nevertheless, performance of this algorithm was not perfect and there was an expectation in providing adequate results with further experimentations. Image segmentation is processed with color and object characteristics, and there was a study focusing watershed segmentation in [15]. The input image is preprocessed with random walk technique to enhance its contrast for effective segmentation. Since the methodology explained in the paper was gradient dependent, the controlled smoothness and minimized energy could not be achieved.

III. PROPOSED WORK

The proposed method for lung cancer detection and segmentation follows three basic diagnostic tasks of radiology namely, preprocessing, classification and segmentation. As stated above, the acquired CT images are preprocessed using denoising function in order to reduce the segmentation drawbacks. Moreover, the noise free image is given for feature extraction process that provides exact classification results. If an image results abnormal, level set-active contour based segmentation model comes into effect to severe the cancer part, which highly supports the oncologist in clinical practice.

1.1 Denoising Analysis

Denoising is one of the Image preprocessing techniques, which is accomplished for effective tumor segmentation. The lung image is denoised by Kernel Based Non-Local Neighborhood denoising method with different denoising functions such as exponential function kernel, cosine function kernel, flat kernel, Gaussian, Turkey-bi-weight and wave kernel function, and then processed with the best kernel function. The resultant image quality obtained by each kernel function is being analyzed with two metrics, Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR). The denoising function that affords result with lesser MSE value and greater PSNR value is considered as the best function for CT image denoising.

The process of denoising analysis against six kernel functions by some quality parameters. The descriptions of kernel functions we used in this proposal are as follows:

a) Exponential Kernel:

$$\boldsymbol{f(x) = e^{\left(-\frac{x}{y}\right)}} \quad (1)$$

λ – Factor to adjust the decay of exponential function.

b) Cosine Kernel:

$$f(x) = \begin{cases} \cos\left(\frac{\pi x}{2\lambda}\right), & 0 < x \le \lambda \\ 0, & else \end{cases} \quad (2)$$

c) Flat Kernel:

$$f(x) = \begin{cases} \frac{1}{x}, & 0 < x \le \lambda \\ 0, & else \end{cases} \quad (3)$$

d) Gaussian Kernel:

$$f(x) = e^{\left(\frac{x^2}{2\lambda^2}\right)}, \text{ for } x>0 \quad (4)$$

e) Turkey-bi-weight Kernel:

$$f(x) = \begin{cases} \frac{1}{2}\left(1-\left(\frac{x}{\lambda}\right)^2\right)^2, & 0 < x \le \lambda \\ 0, & else \end{cases} \quad (5)$$

f) Wave Kernel:

$$f(x) = \begin{cases} \frac{\sin\left(\frac{\pi x}{\lambda}\right)}{\pi x \lambda} & 0 < x < \lambda \\ 0, else \end{cases} \quad (6)$$

MSE Determination:

Mean square error of each kernel function for the input lung image is determined by,

$$MSE = \frac{1}{n \times m}\sum_{i=1}^{n}\sum_{j=1}^{m}\left(x_{i,j} - y_{i,j}\right)^2 \quad (7)$$

PSNR Determination:

The PSNR value for each denoised image is evaluated by,

$$PSNR = 10\log_{10}\frac{1}{MSE} \quad (8)$$

Validating the results of our dataset images on the above-mentioned kernels, the images are denoised with higher PSNR and reduced MSE using Turkey Kernel compared with other. Hence, our algorithm follows this type of denoising function for providing noise free image.

1.2 Feature Extraction

The image feature extraction phase is very substantial in working with image processing techniques, which using various procedures and techniques to detect and isolate distinctive portions or shapes of an image. In this proposal, some valuable characteristics of images such as contrast, energy, entropy, variance and homogeneity are considered that paves a way for appropriate classification results. The noise free image attained from denoising process is fed up into second order histogram based feature extraction, which represents the relative frequency of incidence of various grey levels in an image. The extracted image features are given for classification to identify the lung image is normal or abnormal.

1.3 Classification of Lung Image

By analyzing the extracted features of various CT images of lungs, classification is done by Multivariate Multinomial Distributed Bayes Classification. The multivariate multinomial distribution is congruous for categorical features. The naïve bayes classifier estimates a separate set of probabilities for the set of extracted feature levels in each class, whereas the naïve classifier is applicable when features are independent to one another within a class. The classification is performed in two steps.

Training Step: With the training samples, the method computes the metrics of probability distribution with an assumption that features are conditionally independent.

Prediction Step: For classifying unseen test image, the method estimates posterior probability value of that image belonging to each defined class. Then, the unseen image is classified in accordance with the largest posterior probability value.

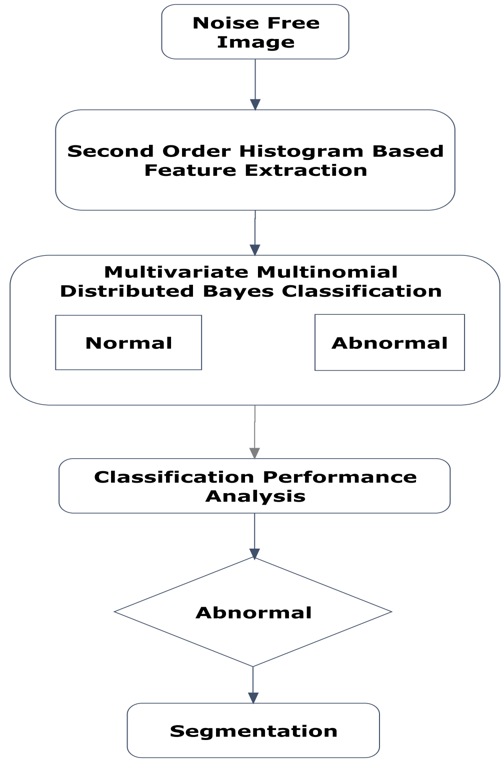

Figure 1: Classification and Segmentation

The block diagram for classification and segmentation is shown in figure 1. From which the unseen test image is categorized under normal or abnormal classes. Classification performance analysis is for the validation of accuracy rate of obtained diagnosis results. The examination is performed with accuracy parameters such as correct/error rate, last correct/error rate, inconclusive rate, sensitivity, specificity, positive/negative predictive value, positive/negative likelihood and prevalence.

1.3 Segmentation using Level set- Active contour Model with minimizer

Our segmentation algorithm is proposed to detect tumor whose boundaries are not necessarily defined by gradient. Energy minimization is the major factor concentrated here. For Curve evolution, Level set Segmentation does not depend on the gradient of an image, whereas Active Contour Segmentation depends on the gradient of the image. The main contribution of the adduced work is formulating Level set equations in such a way that the dependency of active contour on gradient is minimized. The approach is tuned to predict the interior contours automatically. The active contour modeling is to evolve a curve, subject to some constraints. In this proposal, these constraints are formulated using Level set equations. For instance, starting with a curve around the object to be encountered, the curve moves towards its interior normal and has to stop on the boundary of the object. In the classical snakes and active contour models an edge-detector is used, relying on the gradient of the image u_0 to stop the evolving curve on the boundary of the desired object. The Active Contour model is represented as, [11]

$$J1(C) = \alpha\int_0^1 |C'(S)|^2 ds + \beta\int_0^1 |C''(S)| ds - \lambda\int_0^1 |\nabla u_0(c(s))|^2 ds. \quad (9)$$

Here α, β and λ are positive parameters. α and β controls the smoothness of the contour (the internal energy), whereas λ attracts the contour towards object in the image (the external energy).
Depending upon the above equation, the minimization problem is stated as follows.

$$\inf_{C} J_2(C) = 2\int_0^1 |C'(S)|. g(|\nabla u_0(c(s))|) ds \quad (10)$$

By Solving the minimization problem in the above equation consists of finding the path of minimal new length in that metric.

We have implemented a segmentation algorithm that holds the properties of both level set and active contour methods. These methods are unified by making use of a minimizer equation. This minimizer equation is framed in a manner that it achieves minimized energy to plot the contour. The interior and exterior mean calculations and curvature information from the image will support the force of attraction computations.

$$IM = \sum_{(x,y)£(r,C)} \left(\frac{I_{(x,y)}(i)}{length(i)+\varepsilon}\right) \quad (11)$$

$$EM = \sum_{(x,y)£(r,C)} \left(\frac{I_{(x,y)}(e)}{length(i)+\varepsilon}\right) \quad (12)$$

IM= Interior Mean; i = Interior Points
EM= Exterior Mean; e= Exterior Points
ε= 2.2204e-016; I = Image

This force of attraction is necessary to hold the contour in intact position. The force of attraction and curvature value is subjected to compute the energy to be minimized.

$$AF = \left[\left[I_{(x,y)} - IM\right]\right]^2 - \left[\left[I_{(x,y)} - EM\right]\right]^2 \quad (13)$$

$$ME = \frac{AF}{argmax(abs(AF))} * \alpha * C \quad (14)$$

AF= Attractive Force; ME= Minimization Energy; α = 0.2
C= Curvature

The Minimized energy value is manipulated with the automatic generated mask to initialize the evolution of contour.

$$CE = M_{(x,y)} + D * ME \quad (15)$$

CE= Curve Evolution; M= Mask Image; D= Experimental Constant

IV Results and Analysis

For experimentation of the proposed segmentation technique, the CT lung images are obtained from dicom dataset. Hence, the aptness of the proposed approach has been assayed through experimentation on real world CT images. The test data consists of 42 lung images. All the computations are implemented using MATLAB. The lung images are consecutively given for denoising process with different kernel functions and examined with parameters such as MSE and PSNR.

Table 1: Denoising Analysis

Kernel Functions	MSE	PSNR
Exponential	55.6761	30.6741
Cosine	28.0181	33.6564
Flat	90.4523	28.5666
Gaussian	54.0100	30.8061
Turkey	25.2111	34.1149
Wave	26.8877	33.8353

Table 1 represents the denoising analysis, which is made with different kernel functions. According to the computation procedures it is found that input images are denoised with higher PSNR and reduced MSE using Turkey Kernel. Thus, the proposal proceeds with the turkey kernel function for denoising the CT image to acquire highly accurate results.

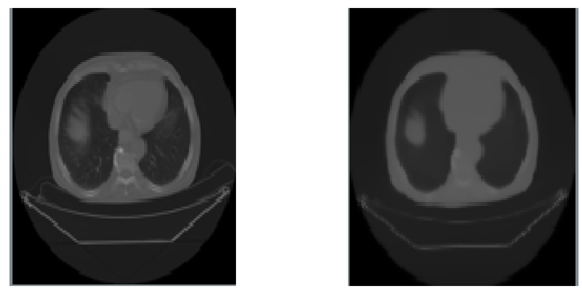

Figure 2: (a) CT lung image (b) Noise free image

The figure 2 (a) implies the input CT image and (b) shows the noise free lung image obtained by turkey kernel function.
The noise free image is then given for feature extraction. This involves in image classification process under normal and abnormal categories. The following table demonstrates the parameters that are responsible for status identification of a single lung image.

Table 2: Feature Extraction

Parameters	Values
Contract	0.0867
Correlation	0.9036
Cluster Prominence	8.7565
Cluster Shade	0.4810
Dissimilarity	0.0860
Energy	0.3704
Entropy	1.3291
Homogeneity	0.9571
Homop	0.9571
Max. Probability	0.5531
Solvb	4.4140
Autocorrelation	4.4332

Providing accurate image classification, the above stated features are extracted and examined for all images.
The confusion matrix (Figure 3) also provides affirmation for the classifier performance along with those metrics. It is generated by the obtained classification results, which reveals the amount of normal and abnormal images categorized using Multivariate Multinomial Distributed Bayes Classification graphically. It is obvious from table 3 that the evaluated

results of false positive and false negative rates are 0. Hence, the accuracy rate achieved by our classification methodology is given as 100%.

Table 3: Classifier Performance Analysis

Performance Analysis Metric	Normal	Abnormal
TP	39	3
FP	0	0
FN	0	0
TN	3	39
Precision	1	1
Sensitivity	1	1
Specificity	1	1

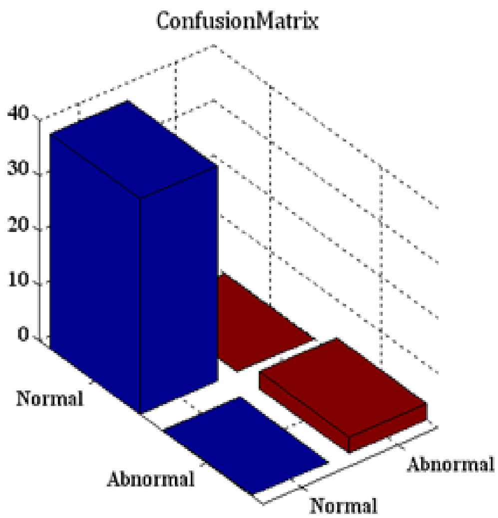

Figure 3: Confusion Matrix

After diagnosis, the segmentation process comes into act to extract tumor mass from abnormal images. The major intention of this proposal is to segment the tumor from an abnormal image using level set –active contour model, which has the ability to detect smooth boundaries over the mass.In order to minimize energy, the curve evolution adopts level set equations with active contour modeling. The extracted tumor assists on finding the exact tumor size and helps in patient's treatment phase. The shape of the tumor mass, determined by segmentation can be used as one of the factors to find whether the tumor is benign or malignant. Figure 4 (a) affords the contour formation based on active contour and level set equations to refine the segmentation. In this proposal, 140 iterations are needed for producing the final, highly precise, smooth results.

V Conclusion and Future Work

In this paper, we have developed a method to segment the lung image, which incorporated active contour modeling and level set equations with minimizer. The combination of two segmentation methods tremendously reduces the computation time and internal energy, and also amends segmentation

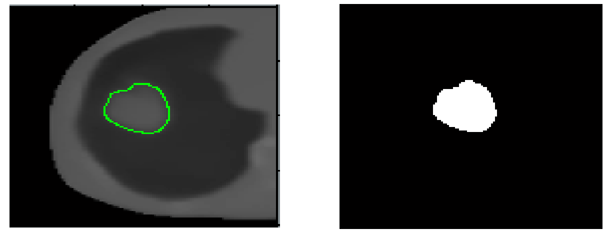

Figure 4 :(a) Contour Formation (b) Extracted Tumor

energy. The location of mass boundaries is well detected and preserved by our method, independent of gradient. Denoising and classification are the core process involved in the proposed system to grab meticulous results. Besides the attainment of producing accurate classification results, the approach has concern with complex and dynamic tumor shapes of the segmentation of CT lung image well in snagging high segmentation accuracy. The adduced method has been processed with 2D image diagnosis and segmentation. As the future work, we plan to expand this methodology for 3D images by developing volume metric depth analysis.

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