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Enhancing Surgical Visualization by Exploring 3D Volume Reconstruction from 2D Slices of CT Lung

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Abstract: In recent years, lung tumor diagnosis and the projection of tumor segmentation in 3D has gained significant momentous in the therapeutic field. Establishing the dissimilarity exists in the three dimensional volume representation of tumor cells affords more information which can sharpen the treatment of a multiplicity of tumors. The volume reconstruction information is indispensable in the case of surgical operations. This process introduces a contour based segmentation algorithm to acquire the appropriate differentiation of pixel boundary that scrutinizes the exact difference between tumor and non tumor cells along the tumor boundary. With the aid of aforementioned formulation, extracted tumor part pixels are reconstructed for the entire 2D slices of the patient data set. Proposal research on 3D voxel reconstruction relies on encountering the isosurfaces. Originally, volume data are subjected to the smoothening process which computes the isosurface data from the smoothened volume data. The generated outcome of this process comprises the vertices and faces of the isosurfaces and directly flows to patch the data. Exploit the 3D reconstructed model to enumerate the voxel damaged by tumor. Proposal research associated with the percentage of damaged voxel along with accurate and reliable perception, simplifies the physician task in lung tumor diagnosis and assist the surgical procedure. Experimental evaluations across the wide range of images show the superiority of the proposed research with the classification accuracy rate of 99.33%.

Key words: Image segmentation, active contours, level set, 3D voxel reconstruction, India

INTRODUCTION

For the past few decades, lung cancer is the leading cause of cancer death. Early diagnosis of lung cancer can maximize the survival rate of tumor influenced person. Therefore, poor long term survivorships of lung cancer increase the obligation for novel methodologies and technologies with respect to lung tumor diagnosis in early stage. When the tumor diagnosing methodologies are hybridized with a utilization of CT (Computerized Tomography) lung screening then the sensitivity and accuracy of primitive stage tumor detection can be relatively enhanced. Image segmentation and enhancement techniques are exploited to accomplish the early stage tumor diagnosis more accurately. Image segmentation techniques segregate the input image into homogeneous regions which affiliates some universal properties. This technique is categorized as region based (examine the uniformity within the sub region) and edge based segmentation (examine the discontinuity in the image intensity). Numerous techniques have been introduced to enhance the performance of image segmentation.

To solve the image segmentation problem, contour based image segmentation algorithm is employed in this research which is supported by active contour and level set equations. Contour based segmentation algorithm efficiently acquires the exact differentiation of pixel boundary. In this segmentation algorithm, user defines the fundamental assumption for the contour and is moved by image driven forces to the contour of specified objects. Contour Based Segmentation Model accommodate internal and external forces. During the deformation process, internal forces specified within the curve aids to keep the model smooth whereas external forces are specified to precede the model toward an object boundary. These external forces are computed only when the underlying image data is known.

In the implementation of active contours, the avail of level set method produce more convenience and flexibility. Level set method is employed to embed a curve within the surface. It acts as a theoretical and numerical tool for propagating interfaces. The intrinsic idea is to begin with a closed curve in 2D/3D and allow the curve to move perpendicular to itself at a defined speed. This way of propagation of contour by exploiting the image properties makes level set method as a frequently used tool in image segmentation.

Three dimensional (3D) reconstructions of medical images have gained an increasing attention. Furthermore,

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reconstruction of 3D volumetric data from 2D slices of patient data set is now an integral part in the field of biomedical research. The voluminous 2D slices registration is of extreme significance for the exact morphometric analysis (volume and surface representation) and 3D visualization. The fundamental principle of 3D reconstruction methods from 2D images is classified into assortion as follows: feature based methods using contours, gray level based registration techniques using the whole image intensities, characteristic points or crest lines elicited from the images, fiducial marker based registration methods. Effective 3D volume reconstruction of image is essential to enhance the pathological visualizations. Moreover, it promotes the value added service and assists the physician.

This research focuses on the lung tumor segmentation and its projection in 3D volume reconstruction. The volume reconstruction information is indispensable in the case of surgical operations. Proposed research introduce contour based segmentation algorithm that acquire the exact dissimilarity between tumor and non tumor cells along the pixel boundary of the tumor. This segmentation algorithm is supported by active contour and level set equations. The formulated curve evolution of active contour and level set method aids to reconstruct the extracted image pixels. The major contribution of proposed research on reconstruction of 3D voxel relies on detection of isosurfaces. The isosurfaces data are computed through smoothening process. It computes a tri-surface geometry of a given volume data at a given isosurfaces value. The outcome of this phase contains the faces and vertices of the isosurfaces that can be passed directly to patch data. The 3D Reconstructed Model is then manipulated to compute the voxel impaired by tumor. This study focused towards a system that builds 3D volume reconstruction an accurate 3D visualization of volumetric data. A complete system would comprises the enumerated components: lung dataset perception, enhancement of perception, preprocessing and feature extraction, classification, image segmentation, patch assignment, 3D visualization of segmented tumor portion, tumor volume calculation.

LITERATURE REVIEW

Medical image segmentation based on the paradigm of deformable contour was illustrated by Kovacevic *et al.* (1999). Compare to the traditional Segmentation Method like region or edge based methods, deformable contour based image segmentation retain many benefits. Deformable contour paradigm is implemented using level set with automatic establishment of active contour original position. This way of image segmentation overcome the limitation occurred in classical region or edge based methods.

Airouche *et al.* (2009) explores the active contour based image segmentation to detect the oil spills in images. Level set method based on partial differential equation denotes the spill surface of the image into propagation interface. Furthermore, speed function is also created by level set method to discover the propagation interface position. Segmentation method exploited in this study produce more reasonable segmentation results than the classical segmentation. It is also possible to divide the contour into multiplex contours with the aim of accomplishing good flexibility in the use of active contours.

In medical image analysis, preprocessing is the fundamental stage in image segmentation. Computer aided diagnosis of lung CT image has gained an increasing attention in the early detection of lung disease. The preliminary step in this kind of diagnosis involves in segmenting the region of interest like lung, heart, brain, etc. The segmentation algorithm proposed by Mesanovic *et al.* (2011) accurately segment the lung parenchyma of lung CT images which assist the physicians in early lung disease diagnosis. Region growing segmentation algorithm selects the seed pixel from the dark side of the image. Once the dark pixels coordinate are selected, pixels which exist in 4-connected neighborhood of the seed pixel are marked. The original gray scale image is segmented into the lungs and trachea after the analysis of region growing.

Another contour based segmentation technique using selective visual attention was proposed by Mendi and Milanova (2010). Visual attention is the term of selecting and getting visual information based on knowledge about objects, scenes and their intersection. The Chan Vese Active Contour Model implemented by this researcher defines the attended location as initial contours. Saliency toolbox employed in this study extracts the attended locations. This method of image segmentation is effective for accurate detection and extraction of ROI (Region of Interest). The integration of these techniques maximizes the speed of segmentation process.

Region based technique presented for image segmentation integrates the information regarding the curvilinear continuity, color and intensity (Leung and Malik, 1998). The soft contour information is obtained through energy orientation whereas weak contrast gaps are completed through contour propagation.

In (Ma and Manjunath, 2000) novel boundary detection and image segmentation technique based on edge flow was presented. The direction of color change and texture at each image location is identified by predictive coding model and then edge flow vector is constructed. In this edge flow technique, identification and localization of edges are performed indirectly. Originally, the flow direction at each pixel location which points to the closest boundary is identified by iteratively propagating the edge flow. Single scale parameter has been used for the implementation of this image segmentation based on edge flow. This scheme attains general framework for combining various kinds of image information for boundary detection.

Another framework for region based image segmentation methodology using Bayesian Level Sets are formulated by Sifakis *et al*. (2002). In this framework, statistical approaches are applied for modeling the different regions. This framework is the extension of the level set approach to a multi label framework which permits the speed of propagation depend on the corresponding region label. Based on the label content description and the region capacity, performance of segmentation is predicted. Propagation speed is maximized by exploiting posterior probability of the corresponding label. Proposed posteriori probability technique yields the optimal segmentation solution which clearly biases the segmentation result.

Huang (2009) proposed a level set method with shape model for image segmentation. The Initial Shape Model is established by manual processing rather than automatically. But depending on the application, Shape Model is initialized. The Initialized Shape Model is dynamically resized and translated. The distance map of Shape Model contour is then established by dilation operation. From the obtained Shape Model, the level set function is updated until the contour converges. This kind of specific shape image segmentation algorithm is widely applicable to temperature image, medical image, etc.

The boundary detection problem can be solved by exploiting numerous techniques developed in recent years. There are some existing boundary detection techniques namely, GAC (Geodesic Active Contours) Model (Caselles *et al*., 1997), ACWE (Active Contours Without Edges) (Chan and Vese, 2001), GVF (Gradient Vector Flow) Model (Xu and Prince, 1997) and ACM (Active Contour Models) (Kass *et al*., 1988).

The most widely used Image Segmentation Method is the active contour which provides sub region with continuous boundaries. The applicability of level set theory in the active contour implementation adds more flexibility in image segmentation. Lee (2005) proposed a robust image segmentation framework which segment the image based on statistics of image intensity. Three Active Contour Models are proposed depends on the method to estimate the mixture density functions. Unsupervised Multidimensional Histogram Method, Supervised Multivariate Gaussian Mixture Density Method, Half Supervised Multivariate Gaussian Mixture Density Method. Integration of both statistical pattern classification and image segmentation in this framework provides autonomous pattern classification.

A novel level set approach for smooth isosurface extraction was proposed by Molchanov *et al*. (2009). This approach works well for both structured and unstructured volume data. Computation of small neighborhood around the zero isosurface of the level set function is mainly concentrated in this novel framework. Since, it provides gradual smooth evaluation of the isosurface during computations. Significant isosurfaces are substantial for provoking advisory visualizations of volume data.

Numerous volumetric reconstruction methods were developed in literature. Among those, reconstruction volumetric 3D model was developed by Eisert (2005). Lorensen and Cline (1987) proposed a high resolution 3D surface construction algorithm. Krinidis *et al*. (2002) proposed efficient algorithm for 3D volume reconstruction from acquired 2D slices. The alignment problem is considered globally on 3D volume which in turn reduces the global objective function. The algorithm overcomes the main limitation of 3D image alignment.

Similarly, a novel framework for the reconstruction of 3D rat brain volume from 2D histological images was presented by Bagci and Bai (2008). This framework works on the basis of three premises. Standard histological images provide accurate 3D volume reconstruction, reliable feature space only is considered for successful registration in consecutive slices, proper selection of reference slice prevents high noise slices and distortion. SDM (Standard Deviation Maps) introduced in this framework estimate the smoothness of 3D volume reconstruction.

Li *et al*. (2010) developed a new algorithm based on PCA (Principal Component Analysis) and demonstrates volumetric reconstruction of 3D images. Using this reconstruction algorithm, information about 3D tumor motion is extracted in real time from a single x-ray projection. Such way of 3D volume reconstruction yields more accuracy and efficiency. Likewise, Dogan (2004) used software called Medical Image Processing and Analysis System for reconstruction of 3D Models of human body by using digital images, CT and MR slices. The fundamental problems in 3D image reconstruction are discussed by Cong and Linh (2002).

Optical flow based registration method was presented by Handels *et al*. (2006) which enhance the quality of image reconstructed from 4D CT data sets. The surface points analyzed from 4D CT data sets associated with 3D computation of lung tumor center displays the appearance of lung tumor in three orthogonal directions.

This study reviewed the progress and limitations of related researches. Examining all those complexities exist in literature, this process propose 3D volumetric data reconstruction from 2D slices of a CT lung image which aids to accurate lung tumor 3D visualization.

PROPOSED METHODOLOGY

Constructing early detection of lung tumor is substantial to ensure the most convenient treatment regime is considered. 3D volumetric data reconstruction works on the principle of physical mechanism which displays points of light within the volume. The reconstructed 3D content uses the display systems as either single rotating display panel or multi-planar display panels. Such, 3D volume reconstruction surmounts the problems imposed by the 2D visualization of data. In this study, 3D reconstruction of volumetric data from 2D slices of a CT lung image is developed which investigate the tumor slices based on the voxel impaired by tumor. The outer section of proposed system is depicted in Fig. 1.

Preprocessing stage: Preprocessing is the most substantial task in medical image processing, aids to enhance the image quality. Preprocessing and enhancement phase in medical image processing,

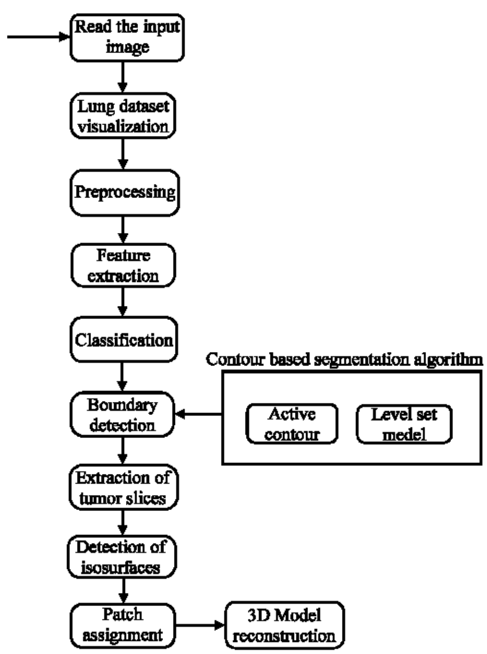

Fig. 1: Proposed system design

regenerate the input CT lung image into standard format with enhancing image contrast, enhancing the sharpening of edges, noise reduction through background removal, image filtering and elimination of film artifacts. The effectiveness of feature extraction depends highly on the image quality. Denoising, a preprocessing technique employed in this paper denoises the CT lung image by Kernel Based Non-Local Neighborhood Denoising Method. Turkey-bi-weight is the supreme denoising function exercised in this proposed research which denoise the lung image and affords noise free image. Turkey bi-weight denoising function furnishes lesser MSE (Mean Square Error) and the higher PSNR (Peak Signal to Noise Ratio). Hence, this kind of denoising function is accorded in this paper to accomplish denoised image. Originally, the lung image is acquired from the dataset then the labels and marks on the image are removed and finally discharge the high frequency components in the image. Preprocessing stage generates the noise reduced and filtered edges of given input lung image.

Feature extraction: Extracting significantly important features from the image data is the ultimate aim in image processing applications. The denoised image obtained from preprocessing technique is supplied into the second order histogram, a feature extraction technique deployed in this research. In this proposal, some valuable characteristics of images like energy, variance, contrast, entropy and homogeneity are considered. These criteria prevail to select the subset of the most essential robust features which simplify the classification result and minimizing entire perplexity.

Lung image classification: The robust image features extracted in feature extraction stage is fed up for classification to distinguish the normal and abnormal status of lung image. In this proposal, the lung image is classified by exploiting Multivariate Multinomial Distributed Bayes Classification. Multinomial Distributed Bayes Classification is one of the two Naive Bayes variants used in image classification which holds the algorithm for multinomially distributed data. For each class x, the distribution framework is represented by vectors:

$$\theta_x = (\theta_{x1},...,\theta_{xk})$$

Here:

k = The total number of features in lung image classification

θ_{xi} = The probability P $(w_i|x)$ of feature i present in a sample belonging to class x

θ_x = The metrics measured by a smoothened version of maximum likelihood

$$\theta_{xi} = \frac{R_{xi}+\alpha}{R_x+\alpha k} \quad (1)$$

Here:

$R_{xi} = \sum_{w \in T} w_i$ = The number of times feature i reflects in the training set (T)

$R_x = \sum_{i=1}^{|T|} R_{xi}$ = The total count of all features for class x

α = A constant

In multivariate distributed bayes classification, distributed data is classified corresponding to multivariate distributions. Precisely, multiple features appear in training data are chosen and make an assumption of each variable as binary valued vector. The classification rule for multivariate distributed bayes classification follows:

$$P(w_i|x) = P(i.w_i|x.w_i)X((1\text{-}w_i) - P(i|x)(1\text{-}w_i)) \quad (2)$$

The multivariate decision rule in a class x explicitly chases the non-occurrence of a features i whereas decision rule based on multinomial classification neglect a non-appearing feature. The classification algorithm exploit in this study evaluate both the above models.

Training phase of naive bayes classifier estimates the parameters of a probability distribution using the training samples, by making assumptions of conditionally independent features. Prediction phase of classifier estimates the posterior probability of unseen test sample and then distinguish the test sample based on greatest posterior probability. Proposed research is trained with 150 slices (51 normal, 99 abnormal) for lung tumor diagnosis and segmentation. The ultimate goal of classification is to examine the accuracy rate of generating results. For that purpose, accuracy metrics like sensitivity, specificity, error rate, correct rate, last error rate, last correct rate, classified rate, prevalence, positive/negative likelihood are validated.

Contour based segmentation algorithm: Boundary detection or image segmentation is the most fundamental process in medical image analysis. In this study, an ultimate technique called active contour based segmentation algorithm is deployed for detecting boundary in lung CT images. The segmentation algorithm incorporates active contour and level set model which acquire the exact dissimilarity of pixels boundary.

The main premise considered with respect to the proposed research is the energy minimization. Active contour based segmentation technique entrusts on the Internal Mean (IM) and attraction of contour towards the object (AF) for curve evolution. On the other hand, segmentation through level set does not entrust on the image gradient. The criterion responsible for curve evolution is formulated with the help of internal and external energy supportive parameters.

Implementation of active contour segmentation in this proposed research provides simple and suitable platform to detect errors and relatively adjust parameters. It is usually deployed to evolve a curve and is subjected to constraints in terms of discovering objects from the given input image. These constraints in active contour modeling are formulated by exploiting level set equations in the proposed research. For instance, initiating with the curve around the object to be distinguished, the curve progress towards its interior normal from the image based on few constraints. Once the boundary of the object is reached, the curve needs to be stopped. Traditional snakes and active contour models used edge detector in existing system to halt the curve evolving on the boundaries of the desired object. This parameter can identify only the objects with edge function exemplified by gradient.

Existing approach u_0 to stop the curve evolution is formed by two regions namely piecewise constant, intensity of distinct value (u_0^i, u_0^0). This criterion produced multiple force term and multiple minimizer term. Moreover, initial formulated curve is not accurate in order to facilitate accuracy in curve evolution it needs to be adjusted under certain constraints. This in turn paves a way for multiple minimizer term. The proposed research surmounts the aforementioned minimize problem by exploring one force term (AF) and one Minimizer term (ME).

Energy minimization equation is framed that accomplishes minimized energy to evolve the contour. The interior and exterior mean calculations drawn in Eq. 3 and 4 and curvature information from the image will support the force of attraction computations:

$$IM = \sum_{(x,y)\in(r,C)} \left(\frac{I_{(x,y)}(i)}{\text{length}(i)+\varepsilon} \right) \quad (3)$$

$$EM = \sum_{(x,y)\in(r,C)} \left(\frac{I_{(x,y)}(e)}{\text{length}(i)+\varepsilon} \right) \quad (4)$$

Here:

IM and EM = The interior and exterior mean

i = Interior points

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. In Eq. 5 and 6:

$$AF = \left[\left(I_{(x,y)}\text{-}IM\right)\right]^2 \left[\left(I_{(x,y)}\text{-}EM\right)\right]^2 \quad (5)$$

$$ME = \frac{AF}{\text{argmax}\,(\text{abs}(AF))} \times \alpha \times C \quad (6)$$

Where:
AF = Attractive Force
ME = Minimization Energy
α = 0.2
C = Curvature

In curvature dependency when the differentiation is equal to the divergence in the curvature, minimized energy value is manipulated with the automatic generated mask to initialize the evolution of contour:

$$CE = M_{(x,y)} + D \times ME \quad (7)$$

Where:
CE = Curve Evolution
M = Mask image
D = Experimental constant

Mask image is obtained by acquiring the differentiation between repetitions of pixels (tumor pixels and tissue pixels) from the image. With the aid of above formulation, the energy minimization problem is solved. Evolving contour for segmentation along with acquired level set equation enhance the image segmentation as more accurate, regarding the tumor volume. Precisely, contour based segmentation algorithm extracts the tumor slices of the lung image. Later, the extracted tumor portion pixels for the entire slices of the patient data set are reconstructed in 3D that makes the visualization of tumor portion more accurately.

3D volume reconstruction: When the segmentation on lung image is completed then next stage is the 3D volumetric reconstruction of tumor slices from the segmented 2D CT images. The proposed research on reconstruction of 3D voxel relies on detection of isosurfaces (Fig. 2). Identification of isosurfaces from volumetric data is the crucial task to obtain the volume reconstruction information. Extended marching cubes and dual contouring is the recently improved isosurface detection algorithm. To construct isosurface from scattered data sets, proposed approach builds on adaptive isosurface detection.

In this proposal, formulation of active contour and level set model intends to identify the isosurface and paves a way for 3D voxel reconstruction. Significant isosurfaces are substantial for provoking advisory visualizations of volume data. Moving towards higher dimension data, the level set contours become level surfaces. These level surfaces are referred as isosurfaces which provokes the initialization of patch data. Patch used on each pixel of the segmented tumor image determines the tumor 3D visualization. Initially, the volume data are subjected to the smoothening process by making use of default convolution kernels. As a result, smoothened volume data is generated. The computation of isosurface data is effectuated from the obtained smoothened volume data. The isosurface value is extracted from the isosurface data for the computation of tri-surface geometry. With the given isosurface value, tri-surface geometry of the volume data is estimated which form the basis for patch assignment. The resultant output generation contains the faces and vertices of the isosurfaces.

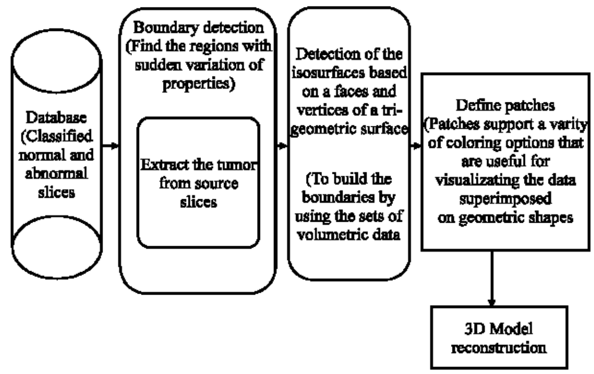

Fig. 2: 3D Model Reconstruction System

Patches support a variety of coloring options that are useful for visualizing the data superimposed on geometric shapes. The segmented tumor slice is split up into multiple patches according to the faces and vertices of the isosurfaces. Since, the isosurface connects points that have the specified value much the way contour lines connect points of equal elevation. Finally, computation of normal is performed for the vertices generated. The 3D Reconstructed Model is then manipulated to compute the voxel impaired by tumor. The percentage of damaged voxel guides the surgical procedure. Finally, tumor volume calculation is percolated to estimate the number of abnormal voxels and percentage of tumor cells.

A system design of 3D Volume Reconstructed Model is exposed in Fig. 3. This input to the system is N slices of 2D tumor slices. Each input slice is processed by proposed system and then the 3D volume reconstruction is percolated which is the core conceit of this study. Apply 3D Reconstructed Model to compute the tumor volume of reconstructed tumor image. The computed tumor size of each slice is then manipulated to acquire the percentage of damaged voxel.

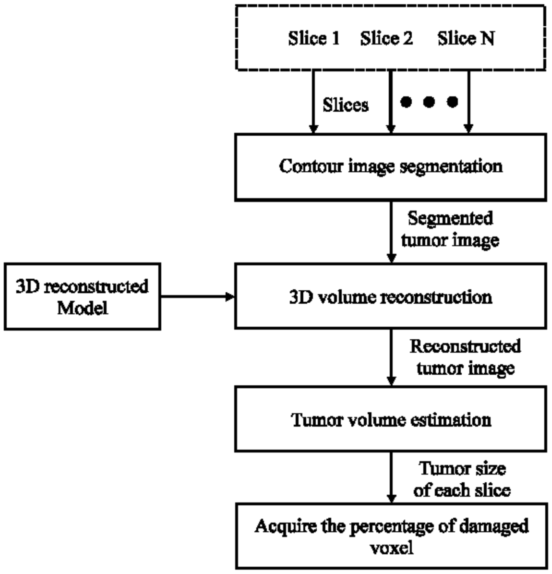

Fig. 3: Tumor volume calculation in 3D reconstruction

Representation of tumor size in 3D is termed as tumor volume which facilitates excellent visualization about the pathological state. The 3D volume construction and visualization introduced in this research allows exploring tumor slices as 3D model. The amount of extracted contour segmented image volume is used to construct the 3D model directly influences its visualization. According to this process, greatest tumor volume increases the vulnerability of lung tumor in patient.

PERFORMANCE EVALUATION

In this study, validation framework is performed to evaluate the quality of 3D volumetric data reconstruction. As an application, proposed method is applied to construct a high resolution 3D model of the lung tumor from 2D slices of CT lung image.

To evaluate the proposed research, experiments is conducted on the entire slices of patient data set. Proposed research is trained with 150 slices (51 normal, 99 abnormal) for lung tumor diagnosis and segmentation. In this analysis, preprocessing and feature extraction is the first procedure that outputs the denoised image along with the subset of most essential features. Figure 4a signifies the input lung image taken for diagnosis, Fig. 4b enhanced lung image after denoising.

The features extracted from denoised lung image are fed to classifier to classify the image as normal and abnormal categories. Performance of classification accuracy is predicted in terms of classification measures namely sensitivity, specificity and accuracy represented

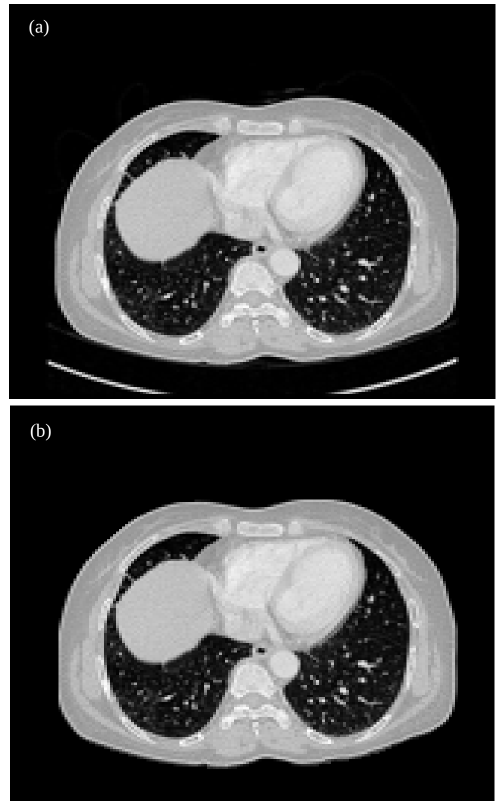

Fig. 4: a) Input CT lung image and b) Enhanced lung image

in Eq. 8-10. True positive/negative and false positive/negative are the balance measures taken into account for classification:

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{8}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{9}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \tag{10}$$

Here:
TN = True Negative
TP = True Positive
FN = False Negative
FP = False Positive

Moreover, confusion matrix affords knowledge related to actual and predicted cases generated by Multivariate Multinomial Distributed Bayes Classification. It is represented graphically by the obtained classification

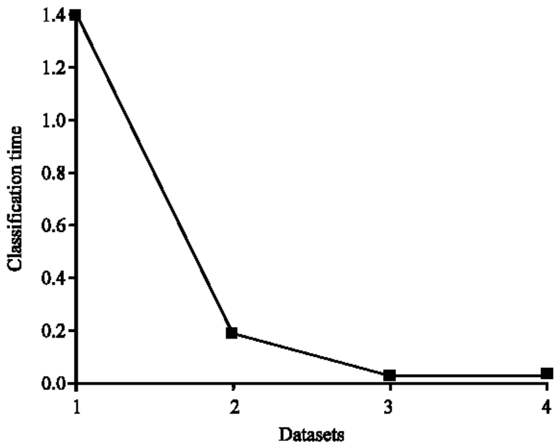

Fig. 5: Classification time of multivariate multinomial distributed bayes classification

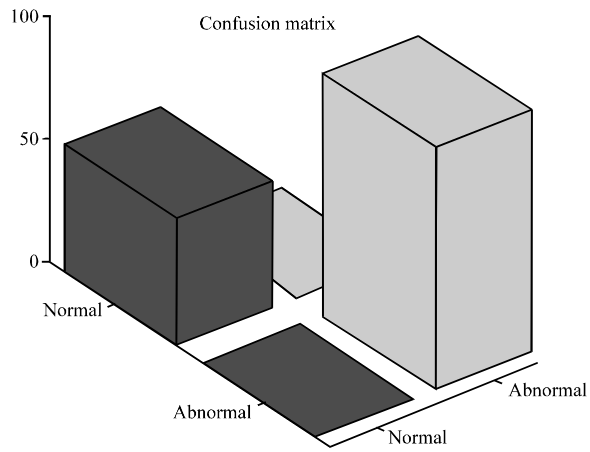

Fig. 6: Confusion matrix

Table 1: Confusion matrix representation

Actual	Predicted: Positive (tumor)	Predicted: Negative (normal)
Positive (tumor)	51	0
Negative (normal)	1	98

results. The classification time taken by this technique for 4 sample data sets is depicted in Fig. 5. Confusion matrix is defined as the format of Table 1.

It is obvious from the Table 1, TP (51) estimate tumor as tumor; FP (0) estimate tumor as normal; TN (98) estimate normal as normal; FN (1) estimate normal as Tumor. The confusion matrix of classification result is drawn on Fig. 6.

Proposed classification system accomplishes the accuracy rate of 99% (Fig. 7). It is evidently proved that classification technique exploited in this process act as a proficient classifier for lung image diagnosis, maximize the accuracy rate by distinguishing the lung image as tumor and normal.

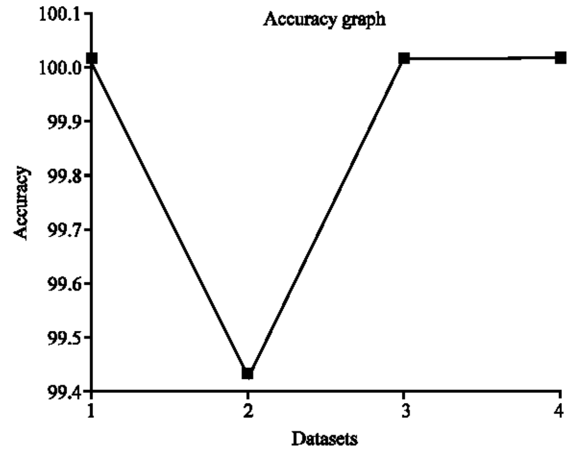

Fig. 7: Classification accuracy of proposed system

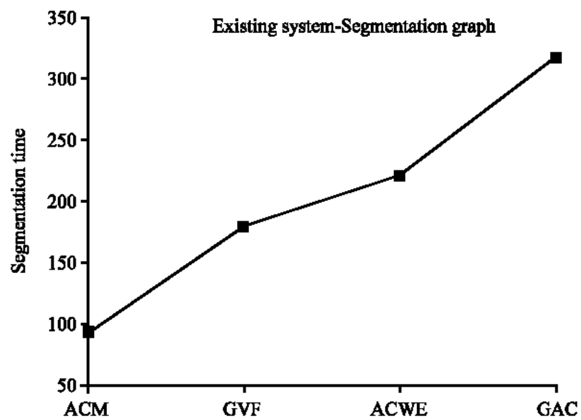

Fig. 8: Segmentation time of existing technique

Once the diagnosis of image is accomplished through proposed method, next stage is the segmentation of tumor mass from abnormal images. The segmentation time taken by existing boundary detection techniques namely, GAC (Geodesic Active Contours) Model (Caselles *et al*., 1997), ACWE (Active Contours Without Edges) (Chan and Vese, 2001), GVF (Gradient Vector Flow) Model (Xu and Prince, 1997) and ACM (Active Contour Models) (Kass *et al*., 1988) is compared with the proposed contour based segmentation technique.

From the Fig. 8, it is obvious that segmentation time taken by existing boundary detection technique is drastically increases. Active contour and level set model deployed in this research enforce to identify the smooth contour towards the tumor mass. Formulation of level set equations integrated with active contour modeling processed in study minimizes the energy by evolving the curve. The tumor mass extracted by the proposed contour based segmentation algorithm shown in Fig. 9 assists the physician in identifying the appropriate tumor size.

Proposed contour based segmentation algorithm require only minimum time when compared with existing boundary detection technique (Caselles *et al*., 1997; Chan and Vese, 2001; Xu and Prince, 1997; Kass *et al*., 1988) to segment the tumor mass (Fig. 10).

The major contribution in this proposal intends in 3D volume reconstruction from the extracted tumor portion pixels. Significant isosurfaces substantial for provoking advisory visualizations of volume data are computed from the smoothened volume data as described in study. The smoothened volume isosurfaces provokes the initialization of patch data as portrayed in Fig. 11. Finally, the 3D tumor visualization (Fig. 12) is reconstructed and are manipulated to estimate the voxel impaired by the tumor.

Tumor volume calculation is incorporated in this experiment by evaluating the highest axis of the tumor along x, y and z orientation. Table 2 affirms the sample tumor size computed in pixels for the segmented tumor portion of image. Measurements like number of abnormal voxels (2095944) and the percentage of tumor cells (40.306615%) in tumor volume computation expose that the proposed system for 3D volume reconstruction works

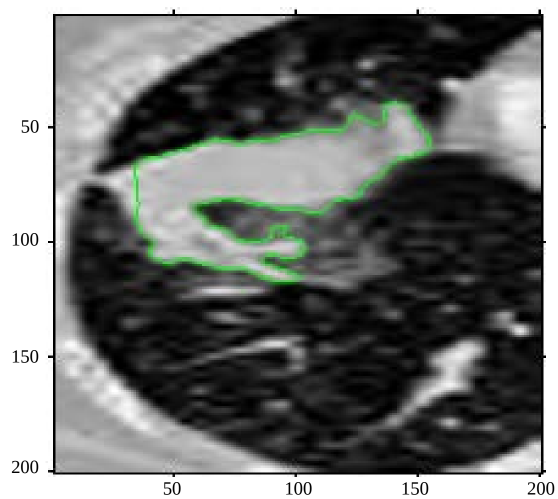

Fig. 9: Tumor segmentation

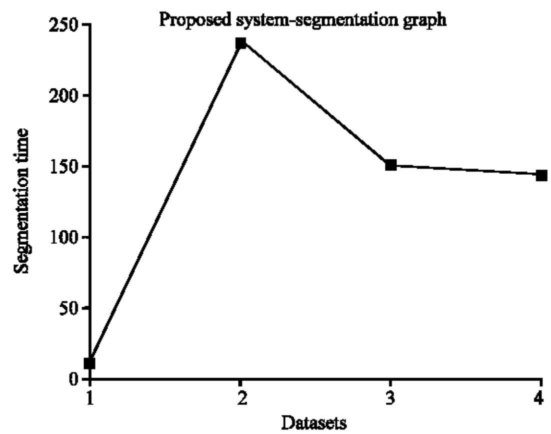

Fig. 10: Segmentation time of proposed contour based segmentation technique

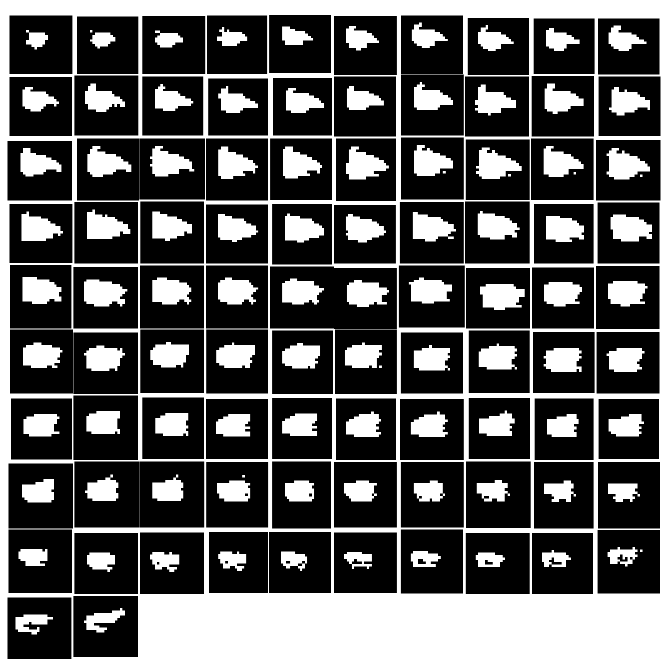

Fig. 11: Patch conversion of extracted tumor slices

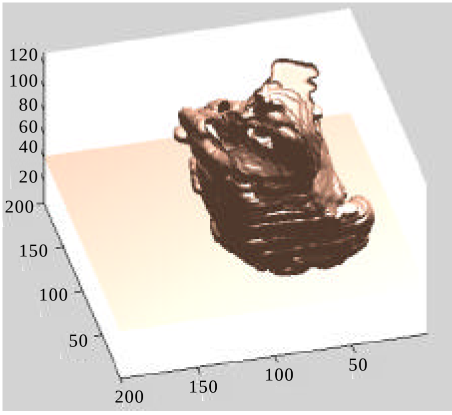

Fig. 12: Tumor 3D visualization

Table 2: Sample tumor slices with tumor size in pixels

Segmented tumor slices	Tumor size (pixels)
1	3098
2	3657
3	4052
4	4341
5	4866
6	4903
7	5285
8	5839
9	5640
10	6492

superior and enhance the tumor diagnosis. With the computed tumor volume visualized in 3D, it is compared with the diagnosis of a physician and then further analysis is conducted.

CONCLUSION

Numerous research have been devoted for 2D image diagnosis and segmentation. In this study, a novel 3D reconstruction of volumetric data from 2D slices of a CT lung image is proposed. The main contribution of the approach involves lung tumor segmentation and its projection in 3D. A contour based segmentation algorithm implemented in this proposal, concentrates on acquiring the exact dissimilarity of pixel boundary. With the aid of active contour and level set model, extracted tumor portion pixels are reconstructed. Proposed 3D volume reconstruction detects the isosurface under smoothening process by computing tri-surface geometry of a given volume data. The 3D Reconstructed Model is then manipulated to compute the voxel impaired by tumor. Empirical results revealed that 3D volume reconstruction system proposed in this study detects 40.30% of tumor volume for the number of abnormal voxels with the segmentation time (S) of 9.5, 235, 149 and142 for 4 sample dataset. The volume reconstruction information is indispensable in the case of surgical operations. The 3D volume reconstruction intended in this study surmounts the problems imposed by the 2D visualization of data.

REFERENCES

Airouche, M., L. Bentabet and M. Zelmat, 2009. Image segmentation using active contour model and level set method applied to detect oil spills. Proceedings of the World Congress on Engineering, July 1-3, 2009, London, UK., pp: 1-3.

Bagci, U. and L. Bai, 2008. Fully automatic 3D reconstruction of histological images. Proceedings of the International Symposium on Biomedical Imaging, April 22, 2008, Nano to Macro, pp: 991-994.

Caselles, V., R. Kimmel and G. Sapiro, 1997. Geodesic active contours. Int. J. Comput. Vision, 22: 61-79.

Chan, T.F. and L.A. Vese, 2001. Active contours without edges. IEEE Trans. Image Proc., 10: 266-277.

Cong, V. and H.Q. Linh, 2002. 3D medical image reconstruction. HCMC University of Technology. http://www.fas.hcmut.edu.vn/webhn10/Baocao/PDF/VCong-Imaging.pdf.

Dogan, S., 2004. 3D reconstruction and evaluation of tissues by using CT, MR slices and digital images. Proceedings of the 20th International Society for Photogrammetry and Remote Sensing Congress, Volume 35, July 12-23, 2004, Istanbul, Turkey, pp: 323-327.

Eisert, P., 2005. Reconstruction of Volumetric 3D Models. In: 3D Videocommunication: Algorithms, Concepts and Real-Time Systems in Human Centred Communication, Schreer, O., P. Kauff and T. Sikora (Eds.). Wiley, New York, pp: 133-150.

Handels, H., R. Werner, T. Frenzel, D. Saring, W. Lu, D. Low and J. Ehrhardt, 2006. Improved reconstruction of 4D MSCT image data and motion analysis of lung tumors using non-linear registration methods. Proceedings of the World Congress on Medical Physics and Biomedical Engineering, Volume 14, August 27-September 1, 2006, COEX Seoul, Koreapp, pp: 2288-2291.

Huang, C.L., 2009. Shape-based level set method for image segmentation. Proceedings of the 9th International Conference on Hybrid Intelligent Systems, Volume 1, August 12-14, 2009, Shenyang, pp: 243-246.

Kass, M., A. Witkin and D. Terzopoulos, 1988. Snakes: Active contour models. Int. J. Comput. Vision, 1: 321-331.

Kovacevic, D., S. Loncaric and E. Sorantin, 1999. Deformable contour based method for medical image segmentation. Proceedings of the 21st International Conference on Information Technology Interfaces, June 15-18, 1999, Pula, Croatia.

Krinidis, S., C. Nikou and I. Pitas, 2002. 3D volume reconstruction by serially acquired 2D slices using a distance transform-based global cost function. Meth. Appl. Artif. Intell., 2308: 390-400.

Lee, C.P., 2005. Robust image segmentation using active contours. Level Set Approaches. http://repository. lib. ncsu.edu/ir/bitstream/ 1840.16/5246/1/etd.pdf.

Leung, T. and J. Malik, 1998. Contour continuity in region based image segmentation. Comput. Vision, 1406: 544-559.

Li, R., X. Jia, J.H. Lewis, X. Gu, M. Folkerts, C. Men and S.B. Jiang, 2010. Real-time volumetric image reconstruction and 3D tumor localization based on a single x-ray projection image for lung cancer radiotherapy. Med. Phys., 37: 2822-2826.

Lorensen, W.E. and H.E. Cline, 1987. Marching cubes: A high resolution 3D surface construction algorithm. ACM SIGGRAPH Comput. Graphics, 21: 163-170.

Ma, W.Y. and B.S. Manjunath, 2000. EdgeFlow: A technique for boundary detection and image segmentation. IEEE Trans. Image Process., 9: 1375-1388.

Mendi, E. and M. Milanova, 2010. Contour-based image segmentation using selective visual attention. Software Eng. Appl., 3: 796-802.

Mesanovic, N., M. Grgic, H. Huseinagic, M. Males and E. Skejic *et al.*, 2011. Automatic CT image segmentation of the lungs with region growing algorithm. Proceedings of the 18th International Conference on Systems, Signals and Image Processing, 16-18 June 2011, Sarajevo, Bosnia and Herzegovina.

Molchanov, V., P. Rosenthal and L. Linsen, 2009. Variational Level-Set Detection of Local Isosurfaces from Unstructured Point-Based Volume Data. In: Scientific Visualization: Interactions, Features, Metaphors, (Series Dagstuhl Fol low-Ups, Vol. 2), Hagen, H. (Ed.). Schloss Dagstuhl-Leibniz Zentrum fur, Germany, pp: 222-239.

Sifakis, E., C. Garcia and G. Tziritas, 2002. Bayesian level sets for image segmentation. J. Visual Commun. Image Repr., 13: 44-64.

Xu, C. and J.L. Prince, 1997. Gradient vector flow: A new external force for snakes. Proceedings of the IEEE Conference Computer Vision Pattern Recognition, June 17-19, 1997, San Juan, Puerto Rico, pp: 66-71.