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Texture Based Watershed 3D Medical Image Segmentation Based on Fuzzy Region Growing Approach

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Abstract
A hybrid multidimensional image segmentation algorithm, which combines region growing and texture based morphological algorithm of watersheds, is proposed. An edge-preserving statistical noise reduction technique is utilized as a stage of pre-processing with the aim of calculation of an exact estimation of the image gradient. After that, a preliminary partitioning of the image into primitive regions is created through employing the region growing. Then watershed is applied. There are few disadvantages in medical image analysis, when watershed is applied after the region growing. The main drawbacks are: over segmentation, sensitivity to noise, poor detection of thin or low signal to noise ratio structures. The real issue of over segmentation is controlled by texture Local Binary Pattern (LBP). The outcomes of the experimentation achieved with two-dimensional/three-dimensional (2-D/3-D) magnetic resonance images are introduced. Numerical validation of the outcomes is given, and exhibited the quality of the algorithm for medical image segmentation.

Keywords: Local Binary Pattern (LBP), Watershed, Medical image analysis.

Introduction

Image segmentation is the issue of partitioning an image in a semantically meaningful way. This vague definition indicates the generality of the problem - segmentation can be found in any image-driven process, e.g. fingerprint / text / face recognition, detection of anomalies in industrial pipelines, tracking of moving people/cars/airplanes, etc. This methodology was broadly used in different departments like medical, traffic, police, satellite & industries. An interesting source of images is the medical field. Here, imaging modalities, for example, CT (Computed Tomography) [1], MRI (Magnetic Resonance Imaging) [2], PET (Positron Emission Tomography) [2], [3] etc. generate a huge amount of image information. Not only the size & resolution of the images grow with improved technology, but also the number of dimensions increases. To obtain compatibility in dimension & to enhance workflow efficiency between imaging systems & other information systems in healthcare environments worldwide, the Digital Imaging & Communications in Medicine (DICOM) [4] standard is made as a cooperative international standard for communication of biomedical diagnostic & therapeutic information in disciplines that use digital images & associated data.

The DICOM standard, which incorporates a file format definition & a network communications protocol, is utilized in handling, storing, printing, & transmitting information in medical imaging. DICOM files can be exchanged between two entities that are equipped to receive image & patient data in DICOM format. Medical images are represented in their raw form by arrays of numbers in the computer, with the numbers indicating the values of relevant physical quantities that show contrast between different kinds of body tissue. Processing & analysis of medical images are convenient in transforming raw images into a quantifiable symbolic [2] form for ease of searching & mining, in extracting meaningful quantitative information to aid diagnosis, & in incorporating complementary data from multiple imaging modalities. One main issue in medical image analysis is image segmentation that identifies the boundaries of objects, for example, organs or abnormal regions (e.g. tumors) in images. Having the segmentation result makes it possible for shape analysis, detecting volume change, & making a precise radiation therapy treatment plan. Recent medical data's are not only in two dimensional, but three dimensional image volumes are common in everyday practice. Even four dimensional data (three-dimensional images changing over time, i.e. movies) are often used. This increase in size & dimensionality provides major technical challenges. So the complexity & information in medical data also increased [14].

In the literature of image processing & computer vision, different theoretical frameworks have been proposed for segmentation. Some of the leading mathematical models among them are Thresholding, region growing [5], edge detection & grouping [6], Markov Random Fields (MRF) [7], active contour models (or deformable models), Mumford-Shah functional based frame partition [8], level sets, graph cut [9], & mean shift [10]. Significant extensions & integrations of these frameworks enhance their efficiency, applicability & precision. These kinds of algorithms that can automatically detect diseases, lesions & tumors, highlight their locations in the large pile of images. The complication in this is we have to trust the results of the algorithms. This is particularly significant in medical applications - we don't want the algorithms to signal false alarms, & we certainly don't want them to miss fatal diseases.

As a result, developing algorithms for medical image analysis needs thorough validation studies to make the outcomes usable in practice. This adds another facet to the research procedure that includes communication between two unique worlds - the patient-centered medical world, & the computer centered technical world. The relationships between these worlds are uncommon to discover & it needs critical endeavors from both sides to join on a common objective. Real medical world has more constraint due to diverse image content, cluttered objects, occlusion, image noise, non-uniform object texture, & other factors. Especially, boundary insufficiencies (i.e. missing edges and/or lack of texture contrast between regions of interest (ROIs) & background) are common in medical images. So, in this paper, we concentrate on introducing two general categories of segmentation methods, the deformable models & the learning-based classification methods, which combine high-level constraints & prior knowledge to address challenges in segmentation.

Related Work

Samual H. Lewis et al. [11] have investigated marker-controlled watershed segmentation for breast tumor candidate's detection. In spite of applying watershed segmentation directly on mammograms, they have a morphological approach to clean up images & then determined foreground & background markers, which attended the issue of over-segmentation & made the watershed segmentation result more reliable.

Boren Li et al. [12] have presented a new methodology to decrease over-segmentation utilizing both pre-and post-processing for watershed segmentation. They have made use of more prior knowledge in pre-processing & merge the redundant minimal regions in post-processing. In the first stage of the watershed transform, this not only generates a gradient image from the original image, but also creates the texture gradient. The texture gradient has been extracted utilizing a gray-level co-occurrence matrix. After that, both gradient images are fused together to give the final gradient image. After the initial results of segmentation, they have made use of the merging region technique to eliminate small regions.

Jingqi Ao et al. [13] have another semi-automated cell segmentation algorithm with a histogram-based global approach with local watershed segmentation. Their process required very little prior knowledge or user interaction. Initial outcome of accurate segmentation of the nucleus from the cell has been presented to determine potential application of the proposed method in cytological evaluation of abnormal nuclear structure.

Lin Yang et al. [15] have presented a robust, fast, & accurate 3D tracking method named as, prediction based collaborative trackers (PCT). They have introduced a new one-step forward prediction to generate the motion prior utilizing motion manifold learning. To obtain both temporal consistency & failure recovery, collaborative trackers have been proposed. They have also presented that in comparison with tracking of detection & 3D optical flow, the PCT offers the best results. The new proposed tracking procedure is completely automatic & computationally efficient. It requires less than 1.5s to process a 3D volume, which contains millions of voxels.

Shanhui Sun et al. [16] have proposed a new fully automated method for segmentation of lungs with such high-density pathologies. The proposed technique comprises of two important processing steps. Firstly, a new robust active shape model (RASM) matching technique which is used to roughly segment the outline of the lungs. The early position of the RASM is found through a rib cage detection technique. In second step, an optimal surface finding method is used to further adapt the initial segmentation result to the lung. In their work, left & right lungs are segmented individually.

Jinghao Zhou et al. [17] have developed an automated lung segmentation technique, which make use of deformable model with sparse shape composition prior for patients with compromised lung volumes with severe pathologies in CT. They have collected fifteen thoracic computed tomography scans for patients with lung tumors & reference lung ROIs in each scan was manually segmented to evaluate the performance of the technique. They first constructed sparse shape composition model using training dataset. After that they have initialized deformable model with SSC prior based on the rough segmented right lung ROI. Next, the right lung with compromised lung volumes is segmented using the robust deformable model. They have fused energy terms from ROI edge potential & interior ROI region based potential are in their proposed model for accurate & robust segmentation.

Bin Chen et al. [18] have presented a new segmentation method of pulmonary blood vessels & nodules. The research work has achieved the first result of segmentation by enhancement filters that are based on local intensity analysis. After that, the initial segmentation results of the blood vessels & nodules into a FSP procedure have combined to perform precise segmentation, which has enhanced the segmentation results significantly. Their outcome has shown that the proposed technique can simultaneously segment both the pulmonary blood vessels & the nodules finely.

Geng-Cheng Lin et al. [19] have proposed a new image segmentation technique, named as Fuzzy Knowledge-Based Seeded Region Growing (FKSRG), for multispectral MR images. In the proposed methodology, fuzzy knowledge comprises the fuzzy edge, fuzzy similarity & fuzzy distance, which are achieved from relationships between pixels in multispectral MR images & has been applied to the modified seeded regions growing process. In conventional regions merging, the final number of regions is unknown. In future, they have proposed a target generation process & applied it to support conventional regions merging, in such a way that FKSRG technique does not over or under segment images. At last, two image sets have been used, specifically, computer-generated phantom images & real MR images in their experiments, to assess the effectiveness of the proposed FKSRG method.

Proposed Methodology

There exists a number of approaches for the segmentation of a medical image. In this approach we have proposed a hybrid method for the segmentation of the lung image. The method is based on the fuzzy region growing algorithm & watershed model based on the texture of the image. The edge detection is carried out by the region growing algorithm. Direct application of watershed segmentation often leads to over-segmentation. This is because of the noise & other local irregularities that lead to large number trivial regional minima. Considering this delimit, the image is to be pre-processed before the application of the proposed algorithm. Block diagram details about methodology is shown in Figure 1 below,

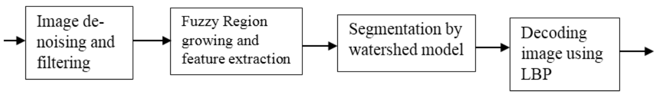

Fig.1. Block Diagram

A. *De-noising & Enhancement of the Image*

Noise that is present in the image degrade the segmentation process resulting in under segmentation or over segmentation. Pre-processing refers to enhancing the quality of the input image by filtering the unwanted artifacts & reducing the noise. This facilitates for improvement in the visibility of the nodules. Numerous filters are used in the pre-processing stage, for example, the median filters, morphological filters, & selective enhancement filter. The Digital Imaging & Communications in Medicine (DICOM) images requires to be reconstructed to enhance the resolution by de-noising the original images

The background noises, for example, black background & artifacts contribute to the inefficiency in identifying the required characters in the image. The aim of the pre-processing is to eliminate background & unwanted artifacts from the DICOM images. In pre-processing of the image the foremost point is to detect the region of interest & crop out the unwanted portion of the image. Simple but computationally efficient methods are adopted in noise reduction. A median filter can be applied to the three dimensional image to suppress the effects of shot noise. The ambiguity in the results because of the uneven & dense background can be reduced by separating the background & the foreground regions by defining the broad area of interest in the image. Threshold can be defined to smooth out the differences in the background by setting the pixels below the threshold value to zero & leaving the pixels with brightness above the threshold unaltered.

The misclassification of the pixel is caused due to the imaging noise, random variations in staining & presence of extra objects. The threshold process may result in some small isolated artefacts due to the presence of dense matter in the background. So it is necessary to remove the minor regions of the noise. The object & the background have varying brightness levels in the original image which may account for the problem such as background corroded with the boundary of the image of interest. De-noising using the filter removes noise in the smooth regions of the image preserving the edges. The image thus produced is free from the speckle noise & impulsive noise. Image enhancement aims at emphasizing the pixel where the local intensity value undergoes a significant change. First the image is converted into grayscale image to reduce the processing time. The noise is eliminated from the original image & provides a better input image for the proposed method by increasing the contrast of the original image. Background separation defines a broad area of interest & reduces the ambiguity due to uneven & dense background. At the end of the pre-processing stage, fine de-noised image is available for segmentation.

B. *Integrating Features for Segmentation by Fuzzy-Region Growing Method*

After completing pre-processing, the fuzzy region growing method is used to apply for further process. There is a necessity to develop algorithms for the segmentation of the DICOM image in three dimensions. Difficulty in the segmentation rises from the variability that are inherent in the biological images & the complexity in the appearance. The main aim is to develop computationally efficient algorithms that are improved versions of the previous methods. The images obtained may not contain well isolated objects, so region based approaches are not suitable for such images. Other cases like simple region growing methods does not show good performance when the images contain high density nuclei & variations in size & shape. To overcome the mentioned limitations a hybrid model is proposed which enhances the accuracy of segmentation. The post processing is detailed in the subsections which includes the nodule detection after the proposed segmentation algorithm is implemented. A hybrid method based on the fuzzy region growing & the watershed model is described. This method states that the pixels within the same neighboring region have almost equal intensity values. The main aim is to group all the pixels which have the similar intensity value to a single region in accordance with the homogeneity criterion. Specifically the region growing method begins with a set of seed pixels that are specified prior. This region, then extended by merging the pixels which possess similar properties in the neighborhood.

The homogeneity criterion accounts for the difference in the intensity value of the pixel under consideration & the average of all the intensities of the region which is previously merged. Once the homogeneity criterion is satisfied the pixel under consideration will be merged with the previously merged region. This segmentation is an iterative process since a pixel will be merged in accordance with the homogeneity criteria at every step. The process is continued unless there are voxels assigned to the region. The region growing process can be divided into region merging & region selection process. The addition of the neighboring pixel to the initial seed region can be termed as the region grows. Selecting the regions from the obtained regions is termed as the selection process. The selection process is done on a predefined criteria & the rest unselected regions are eliminated.

The fuzzy region growing algorithm which is based on the fuzzy rules is employed. The main aim of the algorithm is to split the original image into a numerous homogeneous disjoint regions as shown in equation 1.

$$f = \bigcup_{j=1}^{n} R_j, \qquad R_j \cap R_k = \phi \qquad j \neq k. \qquad (1)$$

Where I represent the image & R the disjoint regions of the image, indicating that the image is composed of the numerous homogeneous disjoint regions. The grouping of pixels or the sub regions into a larger region on the basis of the homogeneity criterion is essential in the region growing process. A segmented region is established by merging the adjacent regions around the pixel under consideration. Segmenting natural images are a combination of appropriate segmentation by considering the intensity features & the fractal dimensional features. The technique of integrating the information of different features is based on the fuzzy rule. The difference & the gradient of the intensities are the considerable features in the fuzzy rule corresponding to each function. Establishing a stronger merging rule is possible for the fuzzy set by considering the fractal dimension feature to achieve a clear segmentation. To conserve the true edges the unnecessary growth of the regions is restricted by employing the boundary edge. The first intensity feature is given by the equation 2,

$$diff = |g_{ave}(R_K) - g(i, j)| \qquad (2)$$

The difference between the average value of the intensity & the intensity value of a pixel under consideration is estimated. If the difference is small then the intensity merges with the neighborhood else it does not merge. The gradient is calculated to achieve an accurate segmentation at lung region. The region growing algorithm avoids the smaller regions which consist of one or two pixels since it prefers large regions. The structures that do not contribute to the detection of the lung nodules are eliminated at this stage. The image consist of only the lung portion of the image which is the region of interest. Only the lung region obtained by this method is used in the subsequent stages of the methodology. The topological gradient is the most suitable tool for preserving the important edges & eliminating all the unnecessary ones. For better segmentation results topological gradient is replaced in the place of the morphological gradient to reduce the set of minima. The next step consists of applying the watershed model using the topological gradient. This fuzzy region growing method removes machinery focuses & unwanted background region. The pre clustered medical data move for the selection of lung portion based on watersheds.

C. *Watershed Model for Segmentation*

A segmentation method is needed for the extraction of the connected components separated by local maxima from the output image of the fuzzy region growing method. The extraction of the lobar regions of the processed image is carried out by the watershed segmentation. The region growing segmentation technique that has the grayscale image input, is analogous to a topological surface is the watershed model. This model works similar to the flooding catchment basins by representing the local minima in the image. Ridge lines formed around each basin separate one region from the other region. Preferably the watershed model is applied to the gradient map of the image than applying directly on the value of the pixels. The model can effectively be performed on the images having low noise. The blurred objects can be detected sufficiently when compared to other simple methods. The medical images have a high noise variance which causes the high density in local minima which leads to over segmentation.

In the proposed method, the watershed algorithm is used for the object separation. The input gray level image is considered as the topographic surface. Each regional minimum is assumed to have punched holes. When the surface is flooded by these holes, the water will eventually flood the set of points whose steepest slope paths reach a given minimum. These points are called as the catchment basins of the image. Each minimum will be completely surrounded by the end of flooding which limits its associated catchment basins. This set of dams corresponds to the watershed surface from the analogy. The input image is provided a tessellation in different catchment basins. The image is then segmented into nuclear & background regions by ignoring the cues in the image. The intensity gradient of the touching nuclei can be interpreted & exploited to perform accurate object separation. The algorithm does not provide other cues for the separation of the touching objects.

There are many advantages of the watershed technique over other previously developed segmentation approaches. The key benefit is the union of all the regions of the entire image region. Moreover, this method is controlled by Local Binary Pattern (LBP) method in every iteration. The watershed segmentation can be applied after the objects & their backgrounds are marked by their regional minimum & the crest lines outlined. The original image is to be transformed if the background is not marked. There are two image transformations to calculate the corresponding contours to watershed lines,

- Distance transform: The transform is purely based on the geometrical shape of the objects.
- Gradient transform: The transform in based on the intensity & the gradients.

Watershed can be defined by the function of its gradient which gives the image edges. The watershed of the swamping gradient of the filtered image is computed. The texture gradient of an image is obtained simply by calculating the gradient of the sub band magnitude & then summing them. The gradient magnitude images are generated in this step. The cleaned image from the previous step is obtained to generate two edge images. These images are used to calculate the gradient image. The input gray level image is considered as the topographic surface. However the texture extraction gives high energy values over the non- textured image intensity boundary. The double edge intensity boundary is resulted by the gradient of the sub band magnitude. Therefore the gradient of each sub band is aimed at step detecting & not edge detection. This makes gradient extraction a simple method to perform the separable filtering on the magnitude of the images & the gradient operator can be described as shown below in equation 3.

$$\Delta f = (f \oplus B) - (f \Theta B) \qquad (3)$$

Where $\oplus$ and Θ denotes dilation & erosion respectively the structuring element is represented as B. Multi-scale gradient is defined for the structuring element when B_i denotes a group of square structuring elements having the size (2i+1) $\times$ (2i+1) pixels.

$$\Delta f = \frac{1}{n}\sum_{i=1}^{n}[((f \oplus B_i) - (f \Theta B_i))\Theta B_{i-1}] \qquad (4)$$

The gradient image is used to represent the characteristics of the local regions to improve the accuracy. The watershed is applied to the gradient of the image for better segmentation. An image Δf is assumed as an element of the space $C(D)$

of a connected domain d & the topological distance between the point p and q is

$$T_f(p,q) = \inf_{\gamma} \int \|(\Delta f)\gamma(s)\| ds \tag{5}$$

Infimum $\inf_{\gamma}$ is the overall path γ inside the domain defines the watershed. The image have a minima $\{m_k\}_{k\in I}$, for some index I & to calculate the catchment basin $CB(m_i)$ of minimum m_i is defined by a set $C \in D$. The catchment basins $CB(m_i)$ are a set of points x in the domain D which are topographically closed to m_i than any other regional minimum m_j.

$$CB(m_i) = \{x \in D \mid \forall_j \in I \setminus \{i\} : \Delta f(m_i) + T_f(x,m_i) < \Delta f(m_j) + T_f(x,m_j)\} \tag{6}$$

The watershed of the image is the set of points that do not belong to any catchment basin. The watershed is then given by the equation,

$$W_{shd}(f) = D \cap \left(\bigcup_{i\in I} CB(m_i) \right) \tag{7}$$

It is sensitive to imaging noise & may result in over segmentation. Hence post processing is necessary after the implementation of the algorithm on the image. The watershed is obtained which consists of the enhanced textural properties of the original image. Finally segmentation with smooth boundaries are obtained through the watershed transform. Once the segmentation of the image is completed the texture of the segmented region analyzed by the Local Binary Pattern operator.

D. *Texture Analysis Based on LBP*

Texture is an essential characteristic of an image & its analysis is an important aspect. An efficient nonparametric texture analysis based on the Local binary patterns (LBP) has been developed. This texture analysis is the measure of the grayscale invariance in a neighborhood. The image is composed of micro patterns which forms the basis for the local binary pattern. The circular derivative of the patterns are produced thru concatenating the binary gradients in the LBP. The edge distribution & the other features in an image is contained in the histogram of these micro patterns. The invariant local grayscale variations information in the image is extracted by the LBP. Computation is done by considering the values of a small circular neighborhood around the value of central pixel. The computation is then done at each pixel location. The texture of the image is then described by the histogram of the images. The patterns can be distinguished on the basis of the transitions namely the uniform pattern & the non-uniform pattern. The uniform pattern is one which has a maximum of two transitions from a zero to one & to choose this patterns a simple rotation invariant bin is used.

A binary code is generated to assign a value to each pixel in an image by thresholding the value of the pixel with the center pixel. Various binary patterns or codes that occur are collected by creating a histogram. LBP operator considers the eight neighbors of a pixel & this basic version can be extended to incorporate all the circular neighborhoods with many numbers of other pixels. This enforces a powerful measure of texture of the image & the results are accurate. The traditional divergent statistical & structural models of the texture analysis are unified in the LBP operator. The method is highly tolerant against illumination changes & its most valuable property is its real world application. The simplicity in the computation makes it possible to analyze any images in real time settings. This method has a large number of applications such as in visual inspection, remote sensing, bio-medical image analysis, motion & face analysis. A remarkable success has been gained in the outdoor scene classification, image recognition & detection. The method is developed for subtracting the background & the objects that are in motion. The texture T in a neighborhood can be defined for a grayscale image as the joint distribution of the gray levels as

$$T = t(g_c, g_0, \ldots\ldots, g_{p-1}), \tag{8}$$

Where
for p+1 image pixels, p>0
g_c is the gray value of the center pixel
$g_p(p = 0, \ldots\ldots, p-1)$ is the gray values of p equally spaced on the circle f radius 'R'
(x_c, y_c) is denoted as the coordinates of the center pixel.
The correlation between the pixels decreases with distance & the textural information in an image can be obtained from local neighborhood. The local texture can be represented without the loss of information as a joint distribution of the value of the center pixel & the differences as

$$T = t(g_c, g_0 - g_c, \ldots\ldots, g_{p-1} - g_c), \tag{9}$$

The distribution can be factorized by assuming that the differences are independent of g_c

$$T \approx t(g_c)t(g_c, g_0 - g_c, \ldots\ldots, g_{p-1} - g_c), \tag{10}$$

The independent assumption may not hold true always in practice. High or low values of g_c will narrow down the range of possible differences due to the limited nature of the values in the digital image. The shifts in the grayscale allows one to achieve invariance with a possible small loss of information. The $t(g_c)$ describes the overall luminance of the image unrelated to local image texture. The useful information for texture analysis is not derived hence a joint difference distribution has to be defined. The equation gives much of the information about the textural characteristics in the original joint distribution.

$$T \approx t(g_c, g_0 - g_c, \ldots\ldots, g_{p-1} - g_c), \tag{11}$$

The occurrences of various texture patterns in the neighborhood of the pixels are recorded by the dimensional difference distribution. The difference closely near to zero for constant or slow varying regions. The differences in some directions are larger than the others at the edges. The differences are affected by scaling though invariant against gray scale shifts. The signs of the differences are considered to achieve invariance with respect to any monotonic transformation of the gray scale,

$$T \approx t(s(g_0 - g_c), \ldots\ldots, s(g_{p-1} - g_c)), \tag{12}$$

Where

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$$

To transform the differences in a neighborhood into a unique LBP code a binomial weight 2^p is assigned to each sign & the equation is given as

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{p-1} s(g_p - g_c)2^p \quad (13)$$

The above equation characterizes the code of the local image texture around (x_c, y_c). The differences in a neighborhood is interpreted as a p-bit binary number which results in 2^p distinct values for the LBP code & the texture can be described by 2p-bit discrete distribution of LBP codes.

$$T \approx t(LBP_{P,R}(x_c, y_c)), \quad (14)$$

Assuming $M \times N$ image samples are given and $x_c \in \{0,.....,N-1\}, y_c \in \{0,..M-1\}$. To calculate the LBP distribution for the image, only the central part is considered since a sufficiently large neighborhood cannot be used in the borders. In the cropped portion of the image, the LBP code is calculated for each pixel & the feature vector is the distribution of the codes denoted as S,

$$S \approx t(LBP_{P,R}(x, y)), \quad (15)$$

The process of identifying the location of the nodules & their type in the lung is known as nodule detection. It is dependent on the accuracy of segmentation methods that are employed. A nodule is almost spherical shaped surrounded by parenchyma & its shape can be deformed by the neighboring surface. We can identify four types of nodules in the lung. They are

- Well-circumscribed: The nodules are found at the core of the lung tissue that are not connected to vasculature.
- Vascularized: The nodules are found at the center of the lung area & are connected to the surrounding lung vessels.
- Pleural Tail: The nodule is present near the surface of the pleural & is connected by a thin structure.
- Juxta pleural: This is the substantial portion of a nodule which is also connected by a thin structure.

In the above mentioned types the well circumscribed type nodules are comparatively easy to identify since they exist isolated in nature. The rest of the other nodules are found attached to the surroundings or other structure which makes the task of detection relatively difficult. Number of nodule detection methods have been proposed for the lung nodule identification. These methods include the morphological processing, template matching, wave front algorithm, rule based method, clustering, gray level & adaptive thresholding & the region growing approach. This proposed method adopts region growing & adaptive threshold for identifying the lung nodule portion. Gray Level Co-occurrence Matrix (GLCM) feature are calculated for every predicted nodules.

Experimental Setup and Result

We implemented our proposed approach of fuzzy region growing method with texture based watershed algorithm to sample 2-D MR images of the lung & obtained general segmentation maps of them. We evaluated the performance of our proposed methodology by comparing the number of partitions in the segmentation map obtained using our proposed methodology against the segmentation maps obtained using the conventional watershed algorithm. These methods identify the tumor region in 44 segmentation. The outcomes of the test results indicated that 90-95% of the initial partitions have been merged; while the other segmentation results disclosed that 85-90% of the initial partitions have been merged. Additionally, we exhibited two sets of segmentation results in Figure 2 – 11.

The use of fuzzy region growing before applying our texture based watershed segmentation algorithm has accomplished the objective of decreasing the issue of over-segmentation when applied to MR images. For instance, applying only the improved watershed method to the image in Figure 4 & 9 will produce a final segmentation map with 65 partitions, but our current methodology is able to produce a final segmentation map of 40 partitions. It can be observed through visual inspections of the segmentation results that there is no visible under-segmentation. However, it can be observed that our proposed procedure has not completely solved the issue of the conventional algorithm & some over-segmentation remains. We separated the two sides of lung portion for analysis. We display two sets of results in Figure 6 & 11. But, the watershed algorithm has its own benefits, compared to these approaches & it has been incorporated in recent work, such as the atlas & improved watershed. Table 1 shows the comparative result of detected tumor region based on Centroid, Eccentricity, Orientation, Solidity, Extent and Perimeter. Solidity, Perimeter and Eccentricity shows the size of lung nodule. If the value of perimeter is less than 5, then it is a small cell nodule whereas it is large cell nodule if it is greater than 5. EquivDiameter shows the location of lung nodule. If the value is higher than 4, it is located on the right side, else it is located on the left side. In our test images, 3 images have nodule in left side, 1 image has it in right side. Our proposed algorithm gives 90% better result than the previous methods using 4 sets of images in different segmentation map.

TABLE.1. Comparative Analysis

GL CM	Cen troid	Eccen tricity	Orien tation	Equiv Diameter	Soli dity	Extent	Peri meter	Run Time in (sec)
Image 1	[6.6,8.3]	0.68	7.8	1.28	0.93	0.71	4.17	4.2
Image 2	[8.1 5.4]	0.70	-2.8	1.08	0.88	0.64	3.81	4.8
Image 3	[7.4 6.5]	0.59	6.3	1.10	0.94	0.68	3.64	3.2
Image 4	[3.6 4.5]	0.74	-7.1	7.2	0.95	0.65	2.21	3.9

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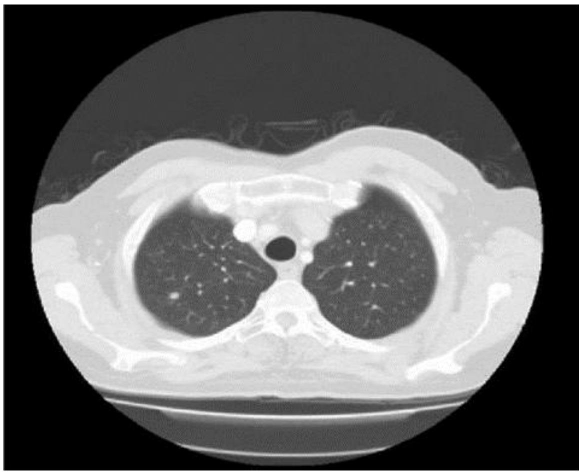

Fig.2. Input Medical Image

Fig.3. Remove Machine Noise

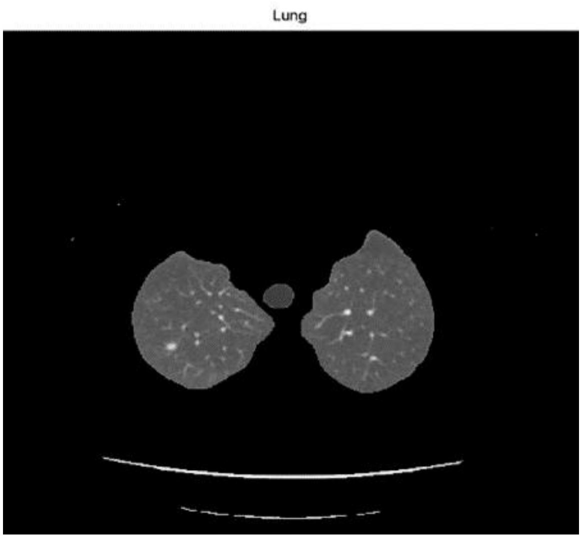

Fig.4. Separate Left/Right Lung Portion using fuzzy region growing

Fig.5. Identify the Possible Nodule using watershed

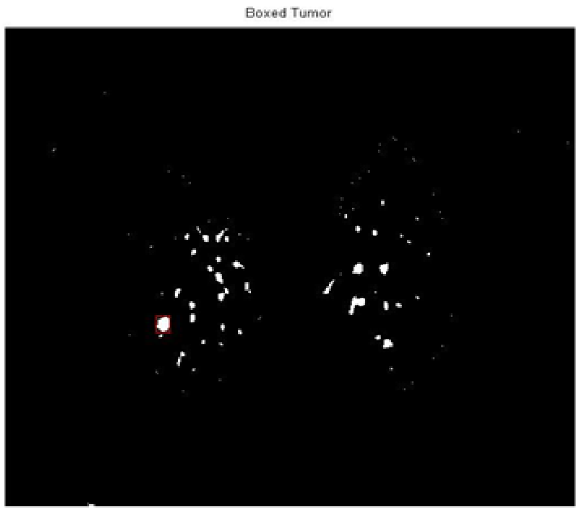

Fig.6. Locate tumor portion using LBP

Fig.7. Input Medical Image

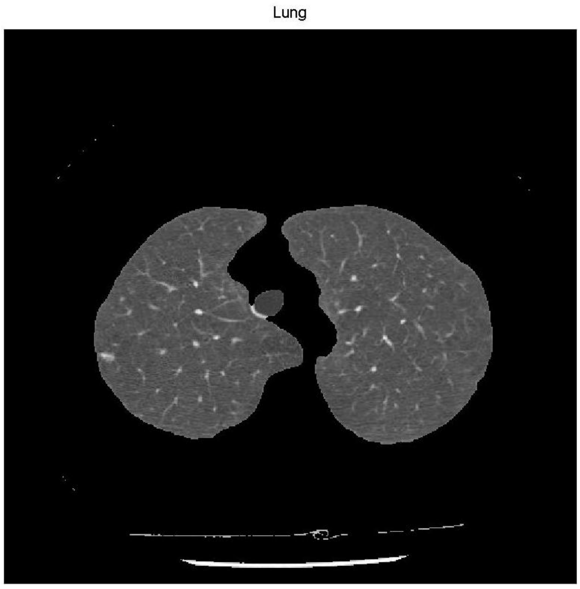

Fig.8. Separate Left/Right Lung Portion using fuzzy region growing

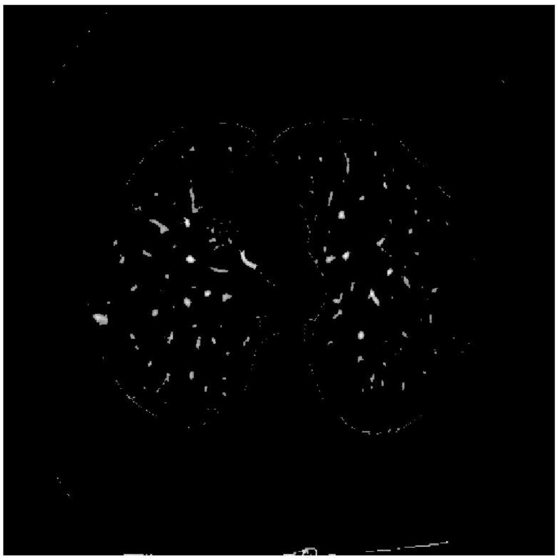

Fig.9. Identify the Possible Nodule using watershed

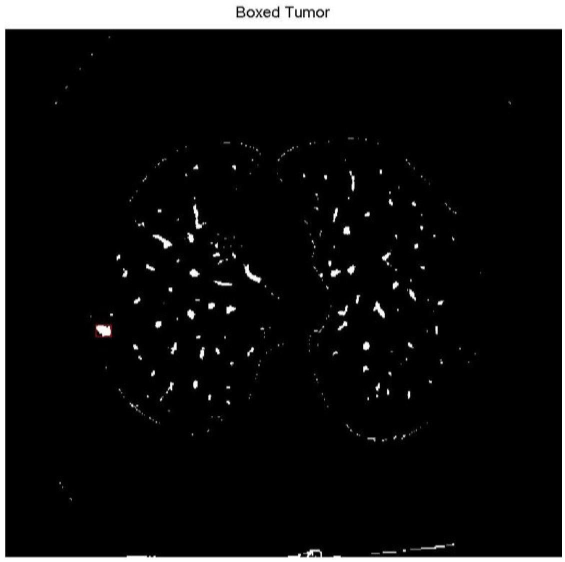

Fig.10. Locate tumor portion using LBP

Conclusion

A fast hybrid segmentation algorithm was presented which incorporates region-based techniques through the watershed segmentation based on a texture based algorithm. The output of the algorithm is the RAG (Region Adjacency Graph) of the final segmentation based on which closed, one-pixel wide object contours/surfaces may readily be extracted. In addition, the RAG provides information about the spatial relations between objects & can drive knowledge-based higher level processes as a means of description & recognition. The overall approach provides a general framework in which gradient & region-based techniques are combined with watershed & LBP. Furthermore, the proposed algorithm is a semi-automated method, and it is not allowed to terminate during the classification time. The proposed segmentation algorithm was implemented for the 2-D & 3-D cases & produced very satisfactory results both with respect to segmentation performance & execution times. However, the memory requirements are relatively high due to the watershed detection algorithm. At last, despite the fact the proposed region dissimilarity function was demonstrated very suitable for near piecewise constant images, the utilization of more complex functions may provide enhanced outcomes at the expense of computational complexity in the time of the merging process. Local Binary Pattern was used for analysis & correction of the resultant tumor portion. However, the computationally efficient extension of the proposed technique to this direction is an open research topic. Forthcoming research is directed toward the improvement of the 3-D version of the algorithm & its extension to the segmentation of moving 3-D images.

References

[1] P. Hua, Q. Song, M. Sonka, E. Hoffman, & J. M. Reinhardt, "Segmentation of pathological and diseased lung tissue in CT images using a graph-

search algorithm," Proc. IEEE International Symposium on Biomedical Imaging: From Nano to Macro, pp. 2072-2075, 2011.

[2] H. R. Marshall, F. S. Prato, L. Deans, J. Théberge, R. T. Thompson, & R. Z. Stodilka, "Variable lung density consideration in attenuation correction of whole-body PET/MRI," Journal of Nuclear Medicine, vol. 53, no. 6, pp. 977-984, 2012.

[3] M. Hofmann, I. Bezrukov, F. Mantlik, P. Aschoff, F. Steinke, T. Beyer, & B. Schölkopf, "MRI-based attenuation correction for whole-body PET/MRI: quantitative evaluation of segmentation-and atlas-based methods," Journal of Nuclear Medicine, vo. 52, no. 9, pp. 1392-1399, 2011.

[4] G. L. Presti, M. Carbone, D. Ciriaci, D. Aramini, M. Ferrari, & V. Ferrari, "Assessment of DICOM Viewers Capable of Loading Patient-specific 3D Models Obtained by Different Segmentation Platforms in the Operating Room," Journal of digital imaging, pp. 1-10, 2015.

[5] B. N. Subudhi, I. Patwa, A. Ghosh, & S. B. Cho, "Edge Preserving Region Growing for Aerial Color Image Segmentation," In Intelligent Computing, Communication and Devices (pp. 481-488). Springer India, 2015.

[6] J. Li, J. M. Bioucas-Dias, & A. Plaza, "Spectral–spatial hyperspectral image segmentation using subspace multinomial logistic regression and Markov random fields," IEEE Transactions on Geoscience and Remote Sensing, vol. 50, no. 3, pp. 809-823, 2012.

[7] J. Chen, J. Li, D. Pan, Q. Zhu, & Z. Mao, "Edge-guided multiscale segmentation of satellite multispectral imagery," IEEE Transactions on Geoscience and Remote Sensing, vol. 50, no. 11, pp. 4513-4520, 2012.

[8] T. E. Chan, & L. Vese, "A level set algorithm for minimizing the Mumford-Shah functional in image processing," Proc. IEEE Workshop on Variational and Level Set Methods in Computer Vision, pp. 161-168, 2001.

[9] A. Belaid, D. Boukerroui, Y. Maingourd, & J. F. Lerallut, "Phase-based level set segmentation of ultrasound images," IEEE Transactions on Information Technology in Biomedicine, vol. 15, no. 1, pp. 138-147, 2011.

[10] D. Ming, T. Ci, H. Cai, L. Li, C. Qiao, & J. Du, "Semivariogram-based spatial bandwidth selection for remote sensing image segmentation with mean-shift algorithm." IEEE Geoscience and Remote Sensing Letters, vol. 9, no. 5, pp. 813-817, 2012.

[11] S. H. Lewis, & A. Dong, "Detection of breast tumor candidates using marker-controlled watershed segmentation and morphological analysis," Proc. IEEE Southwest Symposium on Image Analysis and Interpretation (SSIAI), pp. 1-4, 2012.

[12] B. Li, M. Pan, & Z. Wu, "An improved segmentation of high spatial resolution remote sensing image using Marker-based Watershed Algorithm. In Geoinformatics (GEOINFORMATICS), 2012 20th International Conference on (pp. 1-5). IEEE, 2102.

[13] J. Ao, S. Mitra, R. Long, B. Nutter, & S. Antani, "A hybrid watershed method for cell image segmentation," Proc. IEEE Southwest Symposium on Image Analysis and Interpretation (SSIAI), pp. 29-32, 2012.

[14] S. H. Park, S. Lee, I. D. Yun, & S. U. Lee, "Hierarchical MRF of globally consistent localized classifiers for 3D medical image segmentation," Pattern Recognition, vol. 46, no. 9, pp. 2408-2419, 2013.

[15] L. Yang, B. Georgescu, Y. Zheng, Y. Wang, P. Meer, & D. Comaniciu, "Prediction based collaborative trackers (PCT): A robust and accurate approach toward 3D medical object tracking," IEEE Transactions on Medical Imaging, vol. 30, no. 11, pp. 1921-1932, 2011.

[16] S. Sun, C. Bauer, & R. Beichel, "Automated 3-D segmentation of lungs with lung cancer in CT data using a novel robust active shape model approach," IEEE Transactions on Medical Imaging, vol. 31, no. 2, pp. 449-460, 2012.

[17] J. Zhou, G. Lasio, B. Zhang, K. Prado, W. D'Souza, Z. Yan, & D. Metaxas, "Efficient deformable model with sparse shape composition prior on compromised right lung segmentation in CT," Proc. IEEE 2nd International Conference on In Systems and Informatics (ICSAI), pp. 764-768, 2014.

[18] B. Chen, T. Kitasaka, H. Honma, H. Takabatake, M. Mori, H. Natori, & K. Mori, "Automatic segmentation of pulmonary blood vessels and nodules based on local intensity structure analysis and surface propagation in 3D chest CT images," International journal of computer assisted radiology and surgery, vol. 7, no. 3, pp. 465-482, 2012.

[19] G. C. Lin, W. J. Wang, C. C. Kang, & C. M. Wang, "Multispectral MR images segmentation based on fuzzy knowledge and modified seeded region growing," Magnetic resonance imaging, vol. 30, no. 2, pp. 230-246, 2012.