Fuzzy C-Means and Antlion Optimization Based Segmentation of Juxtapleural Lung Nodules

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Abstract: A Computer aided detection of lung nodules plays a vital role in diagnosis of lung cancer. The aim of this paper is to utilize the characteristics of hybrid Fuzzy C-Means-Ant lion Optimization (FCM-ALO) and morphological operations to extract the juxtapleural lung nodules. The hybrid FCM-ALO based clustering helps in isolating the nodules and boundaries of lung lobes. Morphological operations are then applied to isolate the juxtapleural nodules from the lung boundaries. The proposed method is evaluated using 28 computed tomography (CT) case studies from Lung Imaging Database Consortium-Image Database Resource Initiative (LIDC-IDRI) with 100 juxtapleural nodules. The FCM-ALO based clustering approach gives 0.9464, 0.1575 and 0.2009 as average silhouette index (S), Davies-Bouldin index (DB) and entropy respectively. The sensitivity, specificity and accuracy of the proposed juxtapleural lung nodule segmentation are 99.5\%, 95.03%, and 97.63% respectively.

Keywords: antlion optimization, fuzzy-c-means, morphological operators, juxtapleural nodules, segmentation

I. INTRODUCTION

According to the report in 2015, by World Health Organization (WHO) and International Agency for Research on Cancer (IARC), cancer is one of the major causes of deaths in the world. Some significant agents which cause cancer can be categorized into two types namely internal agents and external agents. The internal agent consists of genetic factors of the human and the external agents include ultra-violet (UV) rays; radiation; chemical carcinogens such as food contaminant, water contaminant, smoke of tobacco and cigarette; and biological carcinogens such as infections from virus, bacteria or parasites. Lung cancer is the most leading lethal type of cancer which causes death of many men and women. The major reasons for lung cancer are high level consumption of cigarette and tobacco, arsenic, metals, fibers, inhalation of dust particles and pollutants from outdoor. According to the key statistics estimation report by American Cancer Society [1], around 224,390 cases are affected by lung cancer out of which 117,920 cases are men and 106,470 cases are women and around 158,080 deaths have occurred due to lung cancer in both men (85,920) and women (72,160).

Pulmonary nodules also called lung nodules play a vital role in detecting signs of lung cancer. A pulmonary nodule is a small and irregular shaped growth in the lung with a maximum size of 3 cm in diameter. If the growth is more than 3 cm in diameter it is more likely to be a cancer tissue rather than a nodule [2]. Detection of lung cancer in the early stages would help in appropriate treatment planning and eventually in curing lung cancer. Diagnosing the characteristics of pulmonary nodules can be done using the de facto medical imaging technique called computed tomography (CT). CT provides an excellent resolution compared to other medical imaging modalities. Though various studies have been carried out in the past few years, still there are challenges in delineating the pulmonary nodules. The delineation of pulmonary nodules is more time consuming and is highly reliant on past experiences of an observer [3]. Hence, there is a demand to build computer aided diagnosis (CAD) system to detect pulmonary nodules and to measure the lung nodule parameters such as nodule size, shape, confidence, subtlety, obscuration, internal structure, calcification, sphericity, margin value, lobulation, speculation, texture and malignancy rate from CT scans [4].

Detection of lung nodules, particularly juxtapleural nodules is quite challenging because it is difficult to 1) differentiate the boundary of juxtapleural nodule & lung boundary and 2) detect the juxtapleural nodules using shape & size properties. In this paper, juxtapleural lung nodules are detected in two stages. In the first stage, Fuzzy C-Means (FCM) and Ant-Lion Optimization (ALO) are combined to segment lung images. In the second stage, juxtapleural nodules are detected from the segmented lung region and nodules using morphological operations. Optimizing FCM with ALO helps in avoiding the local optima of FCM by using ALO's stochastic operator called randomness. The proposed CAD system is designed to reduce the cases of wrongly identified lung nodules and improve the nodule detection rate. The main contributions of this paper are 1) hybrid FCM-ALO based clustering of lung images is proposed which helps in effective clustering of lung regions 2) morphological operations are utilized to correctly detach and extract the juxtapleural nodule from the lung border. The performance of the proposed FCM-ALO based segmentation is determined using measures such as F-score, precision and recall. The rest of this paper is organized as follows. Section 2 describes the work related to segmentation of lung images and detection of lung nodules. Section 3 describes the proposed method using FCM-ALO based lustering and morphological operations for detection of juxtapleural nodules. Section 4 presents the results obtained for clustering of lung images and detection of juxtapleural lung nodules using the proposed method. Section 5 provides the conclusion of this paper.

Revised Manuscript Received on January 15, 2020

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II. RELATED WORK

In the recent years, a lot of research work has been carried out for detecting lung nodules. Badura et al., [5] designed a scheme based on fuzzy connectedness and evolutionary approach for detecting both juxtapleural nodules and solitary nodules. Cascio et al., [6] developed a CAD system for detecting both internal and juxtapleural nodules. The system utilized region growing with opening technique to detect juxtapleural nodules and the segmentation and extraction processes carried out by combing three dimensional (3D) mass-spring model (MSM) with spline curves. Dolejsi et al., [7] developed a system with two different approaches for detecting juxtapleural and parenchymal nodules. The juxtapleural candidate nodules are identified from lung images using closing and thresholding techniques. The candidates of parenchymal nodules are identified using a 3D blob detector based on multiscale filtration and then fitted using ellipsoid model to detect the exact nodules. This system inferred that the classification decreases the false positive rate without affecting sensitivity. Kuruvilla et al., [8] developed the CAD scheme for lung CT images using morphological operations. The Otsu thresholding method is used for lung segmentation and the morphological operations are applied to obtain the nodule regions from the segmented image. Saraswathi et al., [9] designed a CAD scheme using optimal critical point selection (OCPS) and bidirectional chain code (BDC) method for segmenting the juxtapleural lung nodule from the CT images based on its shape and size. The classification of nodules is performed using support vector machine (SVM) and random forest classifiers with the extracted shape and size features. This CAD scheme revealed that the combination of OCPS and random forest classifiers provide best computation results with respect to performance measures compared to other existing techniques.

The methodology proposed by Badura et al. [5] helps in identifying the 3D nodules in an effective manner, but it requires manual marking of the nodule. But, the proposed method is fully automatic in extraction of the juxtapleural nodules. Dolejsi et al. [7] have used thresholding based segmentation and morphological operations to delineate pulmonary and juxtapleural nodules. In the present work, instead of hard thresholding FCM-ALO based clustering is utilized to recognize the regions with juxtapleural nodules. The proposed clustering has advantages such as 1) overcoming local optima due to a good balance between the exploration and exploitation in search space by ALO and 2) improving the clustering accuracy by hybrid FCM-ALO method. Kuruvilla et al. [8] have first segmented the lung lobes and then used morphological operations to segment juxtapleural nodules.The proposed method overcomes this limitation by FCM-ALO based clustering and is able to accurately detect juxtapleural nodules even when the contrast between juxtapleural nodules (foreground) and lung lobes (background) is less. Saraswathi et al. [9] have utilized optimal critical point selection (OPCS) algorithm to find the possible regions of juxtapleural nodules from CT images of 10 patients. ALO utilizes the stochastic parameter called randomness which helps in search process for achieving high exploration capacity than other methods such as particle swarm optimization (PSO) and genetic algorithm (GA) [10]. This characteristics of ALO has been the motivation for using it in the present work. In the proposed work, FCM and ALO are used in clustering phase. The main reason for combining FCM with ALO is to overcome the limitation of local optima of FCM with the help of randomness introduced by ALO. The randomness nature of the ants and antlions are the prominent factor which influences the remaining factors such as exploration and exploitation in the search spaces [10,11]. In the second phase morphological operations are used to separate juxtapleural nodule from lung border.

III. PROPOSED METHOD FOR DETECTING JUXTAPLEURAL LUNG NODULES

In this section, the proposed method to detect juxtapleural lung nodules is described in detail. The proposed method consists primarily of two stages. In the first stage ALO is used to optimize the cluster centers of FCM and these cluster centers are used for segmenting the lung images. In the second stage, morphological operations are carried out on the segmented images to extract the juxtapleural nodules. The proposed method consists of three steps viz., 1) pre-processing 2) clustering and 3) juxtapleural nodule extraction. The block diagram of the proposed method is given in figure 1.

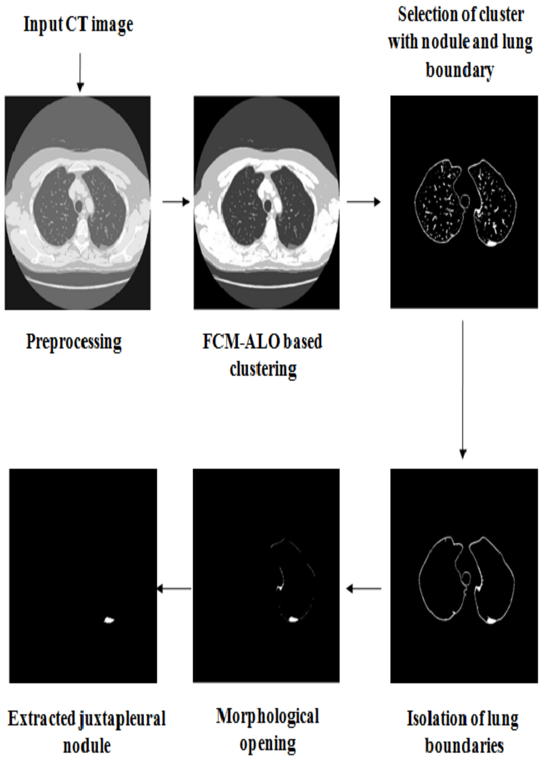


Figure. 1. The steps of proposed CAD

A. Preprocessing

Pre-processing helps in improving the quality of the image for further processing [12]. One of the typical methods used for pre-processing is contrast enhancement.

Contrast enhancement helps in differentiating the nodules and the surrounding normal structures in lung CT images. In the present work contrast-limited adaptive histogram equal ization (CLAHE) is used to enhance the contrast of the lung images. CLAHE helps in limiting the contrast particularly in homogeneous areas to prevent amplifying any noise in the image [13]. The histogram equalized images are given as input for FCM-ALO based clustering.

B. Proposed FCM-ALO based clustering

Fuzzy C-means (FCM) is a well known clustering algorithm which works based on iterative manner [14]. The FCM algorithm utilizes easy rules and there is no need of preliminary parameters for process initialization that identifies the local optimal cluster centres in the search space easily. The main aim of the FCM method is to detect the optimal cluster centres which helps to minimize the dissimilarity function. The FCM has various advantages such as frontward execution, robustness and capacity of handling the uncertainty even though it has some limitations such as lower response to noise in an image and non-attainment of the global optima in search spaces [14]. This can be resolved by combining FCM with any other optimization algorithm. ALO is a recently introduced metaheuristic optimization method which works based on the social behavior of doodlebugs called ant lions [11]. The steps involved in ALO approach are constructing pitfalls; generating the random walks of ants and antlions in search spaces; crabbing ants towards the antlions; catching prey and remodeling the pitfalls; and achieving elitism. In ALO, the exploration capacity can be increased by generating the random walks of ants and antlions in search spaces and the continual adaptation of the antlion's trap can increase the high exploitation in the search spaces. The randomness helps to attain the global optimal solutions in the search spaces. In the present work, the cluster centers obtained from

FCM are optimized using ALO with a modified fitness function. Let $V=\{v_1,v_2,...,v_k\}$ represent the 2-dimensional (2D) slice of lung volume which has to be partitioned into $k(2<k<=N)$ clusters where v_1 is the gray level value of the pixel. The cluster centers for FCM are initialized randomly. FCM aims to minimize the fitness function defined as

$$F_1 = \sum_{j=1}^{k}\sum_{i=1}^{N} u_{ji}^{t}\left\|v_i - C_j\right\|^2 \tag{1}$$

where u_{ji} is the membership value of pixel v_i in the j^{th} cluster, C_j is the center of the j^{th} cluster, $\|.\|^2$ is the Euclidean distance, t is a parameter which controls the fuzziness. For every iteration of FCM, the cluster center is updated based on the distance between the pixels and the cluster centers. The cluster centres C_j are updated using

$$C_j = \frac{\sum_{i=1}^{N} u_{ji}^{t} v_i}{\sum_{i=1}^{N} u_{ji}^{t}} \tag{2}$$

The membership function u_{ji} is updated using

$$u_{ji} = \frac{1}{\sum_{m=1}^{k}\left\{\frac{\|v_i - c_j\|}{\|v_i - c_m\|}\right\}^{\frac{2}{(t-1)}}} \tag{3}$$

The cluster centers obtained from FCM are further optimized using ALO. Let the total number of search agents i.e. antlions of ALO be L. Let each antlion be represented by $X_i = (x_{i1}, x_{i2}, \dots, x_{ik})$ where x_{ij} is the j^{th} cluster centre of i^{th} antlion. One of the antlions are initialized using the cluster centre obtained from FCM i.e. x_{1j} is set as C. The ants move around the search space using random walk given by

$$A_s = [0, cumsum(2r(s_1)-1), cumsum(2r(s_2)-1), \dots, cumsum(2r(s_n)-1)] \tag{4}$$

where

$$(t) = \begin{cases} 1, if\ rand > 0.5 \\ 0, if\ rand \le 0.5 \end{cases} \tag{5}$$

The random walks of ants are normalized using

$$A_l^s = \frac{(A_l^s - a_l)\times(b_l - d_l^s)}{(e_l^s - a_l)} + d_l \tag{6}$$

where a_l is the minimum of random walk for l^{th} variable, b_l is the maximum of random walk for l^{th} variable, d_l^s is the minimum of l^{th} variable during iteration s and e_l^s is the maximum of l^{th} variable at iteration s. The random walk of ants are affected by traps created by antlions which is given by

$$d_l^s = Antlion_p^s + d^s \tag{7}$$

$$e_l^s = Antlion_p^s + e^s \tag{8}$$

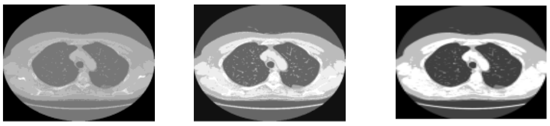
where $Antlion_p^s$ is the position of antlion l at iteration s, d^s is minimum of all variables, e^s is the maximum of all variables, d_l^s is the minimum of l^{th} ant at iteration s and e_l^s is the maximum of l^{th} ant at iteration s. The antlions are selected using roulette wheel selection approach based on their fitness value. The antlion with the best fitness value in each iteration is selected as elite. The random walk of ants are updated using

$$Ant_l^s = \frac{(W_A^s + W_E^s)}{2} \tag{9}$$

where W_A^s is the random walk around antlion selected using roulette wheel at iteration s and W_E^s is the random walk around the elite at iteration s. Ant_l^s is the position of ant l at iteration s. In this paper an improved fitness function for Antlion's optimization is proposed. The fitness function for the antlions is defined as

$$F_2 = \sqrt{\sum_{i=1}^{L}\sum_{j=1}^{k}|x_{ij} - C_j|} \tag{10}$$

where C_j is the j^{th} cluster centre obtained using fuzzy c-means optimization, x_{ij} is the j^{th} cluster centre of i^{th} antlion, |.| represents the absolute operator. The fitness value is obtained for every antlion and the antlion with a smallest fitness value is considered as the elite. The value of elite is considered as the centroids of the required clusters. The proposed method aims to minimize the fitness function given in equation (10). The cluster centre obtained from FCM is further optimized using the proposed fitness function by ALO. The sample segmentation results obtained using the proposed FCM-ALO based clustering are given in figure 2.



(a) (b) (c)

Figure. 2. FCM-ALO based clustering (a) Original image (b) Histogram equalized image (c) Segmented lung image

Juxtapleural nodule extraction using morphological operations

Connected component labeling [8] is used to extract the cluster which contains the nodules and lung border with juxtapleural nodule. Let this region be represented by binary image B with the dimension $Q \times R$ and $N = Q \times R$. The area of all connected components of binary image B is computed using

$$Area_q = \sum_{i=1}^{Q}\sum_{j=1}^{R} B_q(i,j) \tag{11}$$

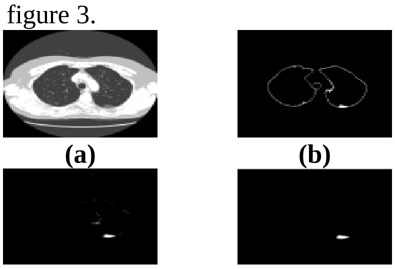
where q represents the q^{th} connected component. The two connected components with the largest area are retained. The retained two connected components with largest areas are usually lung regions in CT images. From these lung regions the borders of the lung regions are extracted. Let the resultant binary image with the extracted borders of connected components be represented by T and structuring element SE be represented by a matrix which is given by

$$SE = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix} \tag{12}$$

A morphological opening operation [5] is performed on T using SE which is given by

$$T \circ SE = (T \ominus SE) \oplus SE \tag{13}$$

where $\ominus$ represents erosion operator, $\oplus$ specifies the dilation operator and $\circ$ represents the opening operator. The resulting image contains blobs among which the one with the largest area represents the juxtapleural nodule. As the morphological opening operation helps in breaking the neck portions in connected components, it helps to extract the juxtapleural nodule detaching it from the lung border. The sample results of lung lobe segmentation and juxtapleural nodule extraction are given in figure 3.



(a) (b)

(c) (d)

Figure. 3. Nodule extraction (a) Result of FCM-ALO based clustering (b) Boundaries of two largest connected components (c) Output of opening operator (d) juxtapleural nodule (largest blob)

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The lung images are gathered from the Lung Imaging Database Consortium-Image Database Resource Initiative (LIDC-IDRI) [4]. The images are in Digital Imaging and Communications in Medicine (DICOM) format. The size of the two dimensional (2D) image is 512×512 and the thickness range of the slice lies between 1.25mm and 2.5mm with the pixel size varying from 0.48mm to 0.72mm. The annotation of the lung images are given in eXtensible Markup Language (XML) files [4]. For the present work, 28 cases with 100 juxtapleural nodules in 100 CT slices are considered. The size of the juxtapleural nodules ranges between 3mm and 30mm. The ground truth details from four radiologists are available in XML files. In this work, the ground truth details provided by the first radiologist are considered for all the 100 nodules. The ground truth details available in XML files for the 100 nodules are used to generate the ground truth images which are saved in portable network graphics (png) format. The proposed method is compared with Otsu [15] based clustering and FCM [14] based clustering. The results obtained using FCM-ALO based clustering are given in figure 4. Figure 4(a) shows the original lung CT image. Figure 4(b) shows the contrast enhanced lung image. Figures 4(c), 4(d) and 4(e) show the clustered lung image using Otsu method [15], FCM method [14] and FCM-ALO based method (proposed method) respectively. The lung images are clustered into 4 regions. Figure 5 illustrates the quantitative evaluation results for Otsu based segmentation, FCM based segmentation and the proposed FCM-ALO based segmentation in terms of structural similarity index (SSIM)[16, 17]. In general, if the original and the segmented image have similar nature they have SSIM values close to 1. In other words, the segmented image with higher loss of structural image has a lesser value of SSIM. The SSIM can be calculated by using the equation 14.

$$SSIM = \frac{(2\mu_v\mu_{\bar{v}} + c_1)(2\sigma_{v\bar{v}} + c_2)}{(\mu_v^2 + \mu_{\bar{v}}^2 + c_1)(\sigma_v^2 + \sigma_{\bar{v}}^2 + c_2)} \tag{14}$$

where μ_v is the average of v (original image), $\mu_{\bar{v}}$ is the average of $\bar{v}$ (segmented image), σ_v^2 is the variance of v and $\sigma_{\bar{v}}^2$ is the variance of $\bar{v}$, $\sigma_{v\bar{v}}$ is the covariance of v and $\bar{v}$, C1 = (s1 · Max limit) 2 , C2 = (s2 · Max limit) 2 , s1 = 0.01 and s2 = 0.03. Figure 6 shows the segmentation of juxtapleural nodules from the lung images. Figure 6(c) shows the resulting clusters obtained using FCM-ALO based clustering method. Figure 6(d) shows the boundaries of two largest connected components or the lung lobes. Figure 6(e) shows the results of morphological opening operation. Figure 6(f) shows the segmented juxtapleural nodule using proposed method. Two methods comprising the same steps as the proposed method but with Otsu based clustering and FCM based clustering instead of FCM-ALO based clustering are implemented. The performance of the proposed method is evaluated based on these two methods. Various standard discrepancy evaluation metrics are utilized to compare the performance of the proposed nodule extraction method with Otsu and FCM based nodule extraction methods. These evaluation metrics are accuracy, precision, sensitivity, specificity [18, 19, 20, 21].

Sensitivity measures the percentage of actual positives values that are properly found whereas specificity measures the percentage of actual negative values which are properly found. In this research work, the obtained average values of sensitivity for Otsu, FCM and proposed FCM-ALO based nodule segmentation method are 88.82±0.079%, 94.13±0.606% and 99.53±0.129% respectively. The obtained average values of specificity for Otsu, FCM and proposed FCM-ALO based nodule segmentation method are 84.80 ± 2.849%, 89.85 ± 2.623% and 95.03 ± 2.409% respectively. The higher sensitivity and specificity values of the proposed method indicate that the performance of the method is good. Accuracy is a measure of correctly classified observations to the total observations. The attained average values of accuracy for Otsu, FCM and proposed FCM-ALO based segmentation are 87.48 ± 0.52%, 92.55 ± 0.38% and 97.63±0.45% respectively. The average values of accuracy of the proposed method is high, hence the proposed method is good. Precision is also known as positive predictive value. The attained average values of precision for Otsu, FCM and proposed FCM-ALO based segmentation are 88.74 ± 0.15%, 94.37 ± 0.64% and 99.89 ± 0.12% respectively. Figure 7 shows the plots of these discrepancy evaluation metrics for the Otsu, FCM and proposed FCM-ALO based segmentation method. Table I compares the results obtained using proposed method with other existing methods in the literature. In terms of sensitivity the proposed method is more efficient than Kuruvilla et al.[8], Senthilkumar et al. [21] and Sariya et al. [20]. In terms of accuracy the proposed method is more efficient than Sariya et al. [20].

Original lung CT image	Histogram equalized image	Otsu based clustered image	FCM based clustered image	FCM-ALO based clustered image

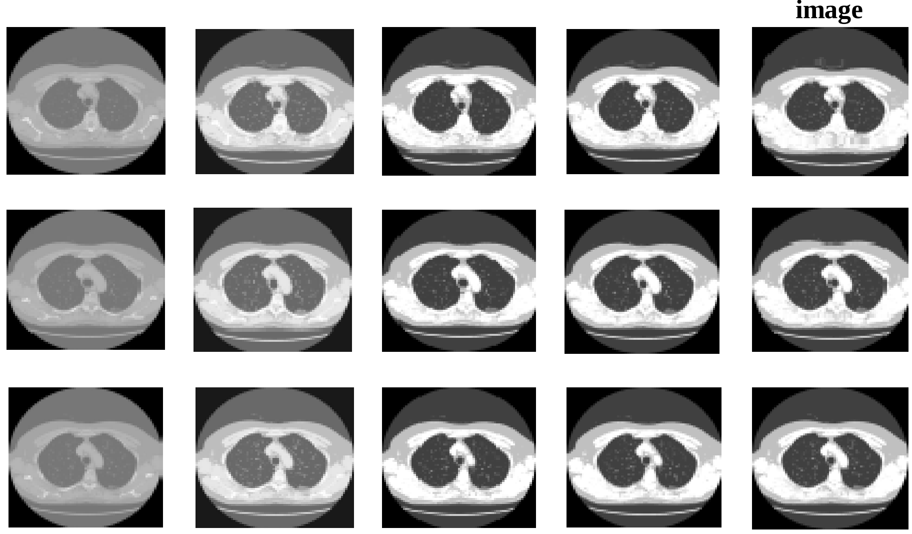


Figure. 4. Results of clustering using Otsu method, FCM method and FCM-ALO method

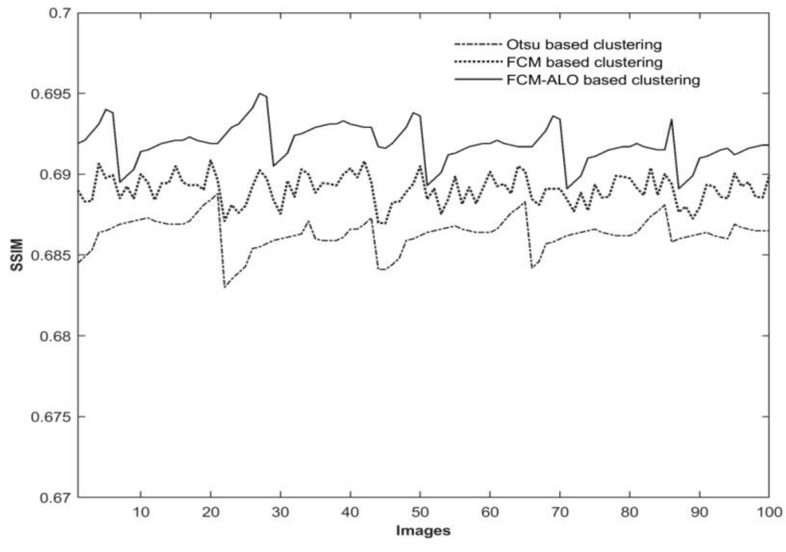


Figure. 5. Comparison of various image qualitative measures for Otsu, FCM and FCM-ALO based segmentation using Structural Similarity Index

Original lung CT image	Ground truth	FCM-ALO based clustered image	Boundaries of two largest connected components	Output of opening operator	Extraction of juxtapleural lung nodule

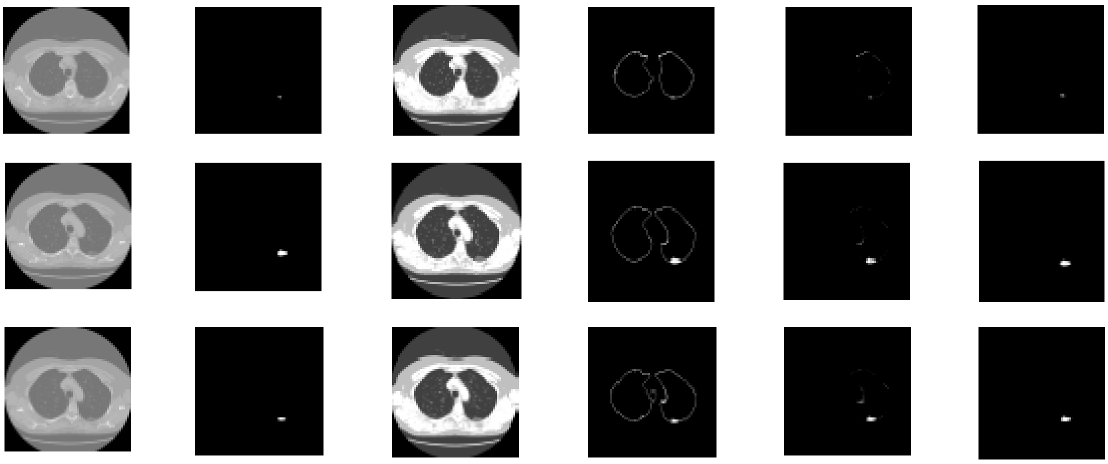


Figure. 6. Results of juxtapleural nodule segmentation

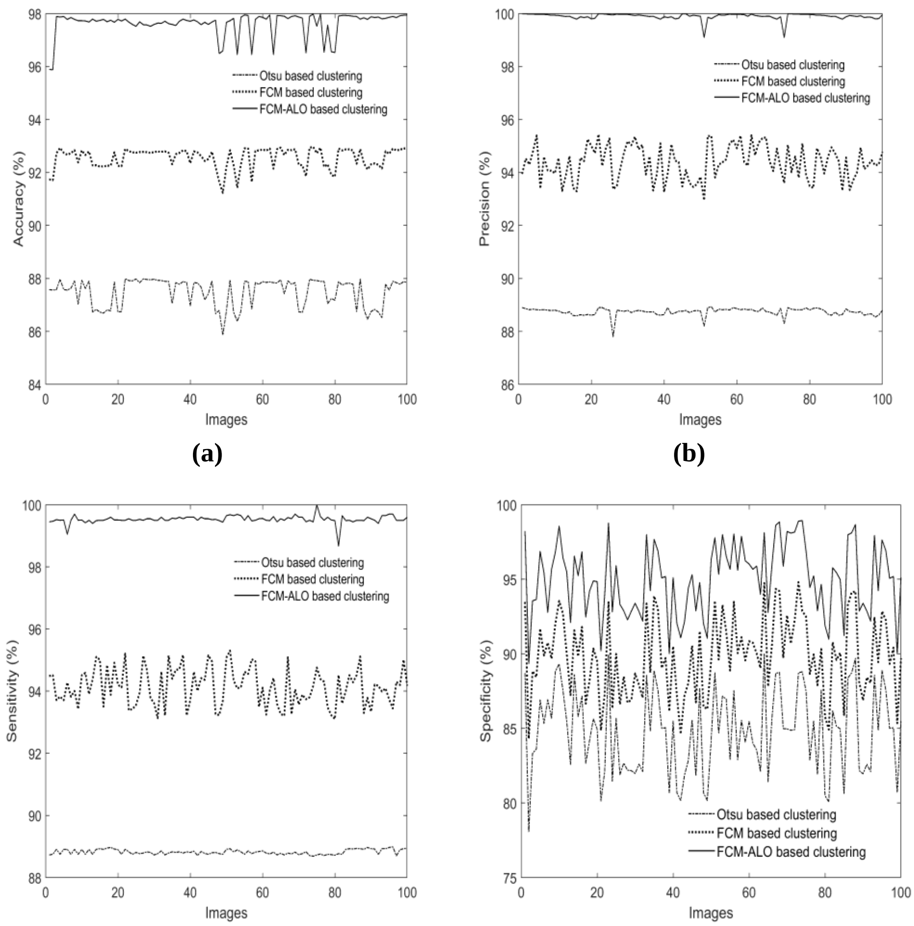


Figure. 7. Comparison of Otsu, FCM and FCM-ALO based segmentation using discrepancy evaluation metrics (a) Accuracy (b) Precision (c) Sensitivity (d) Specificity

Table I: Performance Comparison with existing works

Method	Datasets	Sensitivity %	Specificity %	Accuracy %
Dolejsi et al., [7]	Somatom AR Star CT machine Siemens	95.90	-	-
Kuruvilla et al., [8]	Lung Image Database Consortium (LIDC) and also from reputed hospitals	88.24	93.33	90.63
Sariya et al., [20]	Lung Image Database Consortium (LIDC)	88.00	-	83.00
Senthilkumar et al., [21]	SPIE American Association of Physicists in Medicine (AAPM) lung challenge database and Lung Image Data Consortium (LIDC) database	88.00	84.05	-
Proposed method	Lung Image Database Consortium (LIDC)	99.53	95.03	97.63

V. CONCLUSION

Segmentation of lung nodules from lung images is a preliminary step in diagnosis of lung cancer. In this paper, hybrid FCM-ALO and morphological operators based juxtapleural nodule segmentation is proposed. The hybrid FCM-ALO is used for clustering the lung images from which the lung borders with juxtapleural nodules are extracted. Later, morphological operations are applied to separate and extract the juxtapleural lung nodules. The experimental results indicate that the performance of the proposed method is comparable with other existing works. The proposed method has a great scope in accurate detection of juxtapleural lung nodules.

The main strength of the present work is usage of FCM-ALO to overcome the local minima in the image clustering stage. This is due to the fact that ALO has a good exploration capability. In the present work, segmentation of juxtapleural nodules is performed on 2D lung images only. In future, 3D segmentation of nodules will be carried out. The present work segments only juxtapleural nodules. It will be further extended to segment pulmonary nodules also.

ACKNOWLEDGEMENT

The authors are thankful to Bharathiar University for valuable support. The first author is also thankful to Bharathiar University for the grants provided through University Research Fellowship scheme.

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