

Research Article

Segmentation of Lungs via Hybridization of CA and Level Set Algorithm

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Abstract: In this study, we present a fast and robust practical tool for segmentation of solid tumors with minimal user interaction. The lung image is segmented manually by the experts may includes risk and time consuming process. Hence, in this study, the lung image is segmented in order to identify the tumor sector. Initially, the input lung image is applied with the denoising process for removing noises with the aid of multi-wavelet transformation. After this process, the CA algorithm is applied for obtaining the background seeds and foreground seeds (tumor seeds) and then the level set algorithm is applied for acquiring the acute tumor tissues. As a result of the mentioned process, the tumor sector is segmented and the results are depicted. Studies on lung tumor datasets demonstrate 80-85% overlap performance of the proposed algorithm with less sensitivity to seed initialization, robustness with respect to heterogeneous tumor types and its efficiency in terms of computation time.

Keywords: Background seeds, CA (Cellular Automata) algorithm, foreground seeds, level set algorithm, lungs, segmentation, tumor

INTRODUCTION

The medical imaging is a gifted technique to be aware of the physical condition of different organs of human body. There are numerous techniques available such as digital radiography (X-ray), Computerized Tomography (CT) and Magnetic Resonance Imaging (MRI), which are being applied on patients 'bodies based on different diseases (Hasan *et al.*, 2012). Analysis of medical images is frequently intricate and time overwhelming, even for skilled physicians. The support of image analysis and machine learning can make this process easier (Agarwal *et al.*, 2010). Computer aided radiological diagnosis frequently involves an analysis of individual anatomical structures, location of pathological regions and extraction of various features describing texture and size. Image segmentation, playing a crucial role in plentiful applications, relies on the extraction of homogeneous and non-overlapping regions (Wieclawe and Pietka, 2012). Image segmentation is the task of splitting a digital image into one or more regions of interest (Mostofi, 2009). Segmentation is defined as partitioning portions of an image. It adds structure to a raw image (Dhole *et al.*, 2013).

Lung disease is one of the foremost causes of death. Some evidence suggests that early detection of lung disease may allow for timely therapeutic intervention which in turn results in a more favorable

prognosis of the patients (Krishnan and Robinson, 2013). Numerous computer-aided lung image analysis methods require the segmentation of lung tissue in an initial processing step (Sun *et al.*, 2010). Lung diseases are a few of the most widespread medical conditions worldwide. Tens of millions of people experience from lung disease worldwide. Smoking, infections and genetics are in charge for the majority lung diseases (Mesanovic *et al.*, 2011). Lung cancer is one of the most serious cancers, with the smallest survival rate after the diagnosis, with a gradual increase in the number of deaths every year. Survival from lung cancer is directly related to its growth at its detection time. The earlier the detection is, the higher the chances of successful treatment are. An estimated 85% of lung Cancer cases in males and 75% in females are caused by cigarette smoking (Sharma and Jindal, 2011). For providing solution to this issue, the prognosis of lung cancer is a vital one. In order to make prior diagnosis, the segmentation of lung tumor is a crucial process.

As discussed earlier, in order to identify the lung tumor, segmentation is the vital step and various researches have done in this field. A few of them are listed below. In Hashemi *et al.* (2013) have meant that at detecting lung nodules automatically throughout Computerized Tomography (CT) image. For that reason, they have offered a technique to develop the efficiency of the lung cancer diagnosis system, through a region growing segmentation method to segment CT

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scan lung images. Afterwards, cancer recognition was presented by Fuzzy Inference System (FIS) for differentiating amid malignant, benign and advanced lung nodules. They have examined the diagnostic performances of FIS system through Artificial Neural Networks (ANNs). In Sasidhar *et al.* (2013) have concerned two steps a. Automated Segmentation of lung regions b. Automated Detection of lung cancer. For speeding up the process of detecting lung cancer, segmentation of lung region plays an important role. The proposed algorithm has assisted the radiologist for the better diagnosis of lung cancer. An Automated approach has been exploited to spot lung cancer.

Sharma and Jindal (2011) have presented a system for early recognition of lung cancer by analyzing lung CT images using several steps. The approach had been started through extracting the lung regions from the CT image using several image processing techniques, including bit image slicing, erosion, weiner filter. They have established the using of bit plane slicing technique instead of the thresholding technique that was utilized in the initial step in the extraction process to convert the CT image into a binary image. Bit-plane slicing technique was both faster and data-and user-independent compared to the thresholding technique. After the extraction step, the extracted lung regions were segmented using region growing segmentation algorithm. Then, the initial lung candidate nodules resulting from the Region growing segmentation were analyzed to extract a set of features to be used in the diagnostic rules. These rules were utilized to detect cancerous region and also have obtained the result. In Siddique *et al.* (2014), have presented a method to automatically detect both tumors and abnormal lymph nodes simultaneously in Computerized Tomography (CT) thoracic images. They have performed the detection in a multistage approach, by first detecting all potential abnormalities and then they have differentiated between tumors and lymph nodes. Then lung tumors were categorized as benign and malignant using ANFIS by measuring the parameters like precision, recall and sensitivity. Wide range of researches is carried out in this field and in our study, the input image is selected with initial seeds randomly and then these seeds are applied with the CA algorithm for the computation background seeds and foreground seeds (tumor seeds). Subsequent to this process, level set algorithm is applied in order to obtain the acute tumor.

MATERIALS AND METHODS

The impact of Digital Image Processing (DIP) is on various fields such as medical, surveillance, engineering applications, astronomy and more. Besides other, in the medical field the exploitation of digital image is bowled over. The digital images are utilized as

the initial step of analyzing the diseases that supports the medical practitioners for providing treatment to the patients. In medical field, the digital image plays a crucial role by diagnosing and identifying the stages of diseases in order to heal them. In the proposed method, the digital image is utilized to segmenting the lungs region in order to separate the affected regions. Segmentation is defined as partitioning portions of an image. It adds structure to a raw image (Chen, 2008). In order to detect the pathological abnormalities presented in the lungs, the segmenting its anatomical parts is the vital step.

In the proposed methodology, the hybridization of CA and the level set algorithm is utilized. The introduction of both the methods is detailed in the section. Initially, the digital image of lungs is obtained through the modern acquisition techniques. It may have noises either because of the devices or the acquisition techniques and hence the digital images are applied with the denoising technique. After this process, the denoised digital lung image is applied with the CA algorithm for obtaining the clear-cut view of the background and foreground particles. Then the tumor strength is computed and after that to obtain the acute tumor tissue, the level set algorithm is applied in it and hence the segmented regions are obtained. Some of the researches are available in this lungs segmentation for examining the tumors, rather than the other researches the proposed method obtains the required output without the aid of manual perception.

Let I_m be the digital image of lungs with the size of $M \times N$ and may acquired through the modern acquisition techniques, $I_{m,n}$ where $0 \leq m \leq M-1$ and $0 \leq n \leq N-1$. This image I_m is utilized for segmenting the tumor region and this is further exploited for the classification and hence the image must be clear without the presence of noises. For removing the noises in the image, the multi-wavelet transformation (Mohideen *et al.*, 2011) is applied and the steps are below:

- Step 1:** The image I_m is decomposed via multiwavelet transformation (Velayudham and Kanthavel, 2012) and the decomposing level is δ .
- Step 2:** The energy distribution of every small sub bands are computed statistically.
- Step 3:** Initial threshold is computed.
- Step 4:** The threshold of each sub band is fixed and the wavelet coefficient of every level is computed.
- Step 5:** By performing the inverse multi-wavelet transform through the above process repeated using the high and low frequency coefficients and finally the denoised image I_g is obtained. Then the denoised image I_g is applied with the CA algorithm in order to obtain the background and the foreground regions. For this process, let Gr be the graph that contains

vertices vr and edges ed , a weight w_{ij} is assigned to each edge between the vertices. Here the image I_g pixels are the vertices and edges are the similarity measure (i.e., color/gray level intensity values) between the neighboring pixels. Each vertex vr has an attribute z that is an indicator of the probability of a label, here label is the background and the foreground label and the initial seeds are

chosen randomly. The randomly selected seeds are compared with the reference values (an array of tumor seed's value). These initial seeds are selected and then the foreground and background seeds are computed based on the reference value. Then the foreground and background seeds are applied with the CA algorithm through the region around the selected seeds.

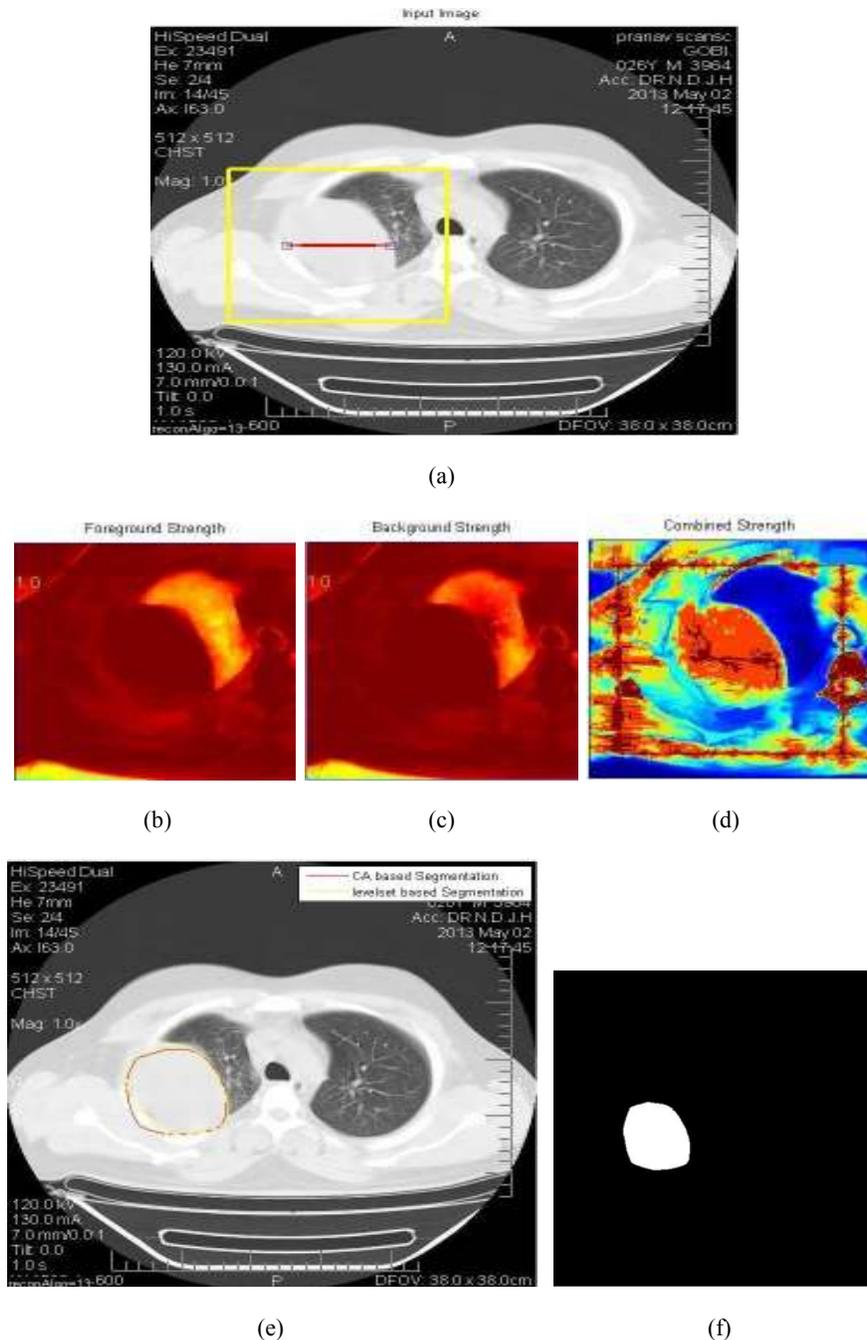


Fig. 1: (a) Input lung image, (b) foreground strength of the input image, (c) background seed strength, (d) combined strength of background and foreground strength, (e) segmentation using CA (red), segmentation using level set (yellow), (f) segmented lung tumor

Once the region is selected then the CA algorithm is running twice on this region in order to identify the tumor presented in the lungs. CA algorithm has its own transition rules for spotting the tumor area. According to these transition rules, the pixels changes its state synchronously that depending on their neighbor pixels. After completing this process, the 2 sets of strength maps are computed and they are background and foreground strength maps. Once the strength maps are combined then the probability map is determined. Initially the seed value is initialized and then the previous state is copied to a new variable. Once the state has been changed then the process is applied. The following algorithm shows the aforementioned process. After that the equation for combining strength map is showed in (1):

```

For  $\forall lb \in \{Tr, Bg\}$ 
//Initialize
  For  $\forall px \in P$ 
    If (px is a seed of label lb) then
       $z_{lb,px}^0 = 1$ 
    Else  $z_{lb,px}^0 = 0$ 
    End if
  End for
Do until convergence
//For each cell
  For  $\forall px \in P$ 
//Neighbors try to attack current cell
  For  $\forall qx \in N(px)$ 
    Find qx* : qx with maximum  $g(px, qx) \cdot z_{lb,qx}^t$ 
     $z_{lb,px}^{t+1} = g(px, qx^*) \cdot z_{lb,qx^*}^t$ 
  End for
  //copy previous state
   $z_{lb,px}^t = z_{lb,px}^{t+1}$ 
End for
End do
End for

```

After the CA algorithm, the obtained strength maps (i.e., foreground and background seed's strength maps) are combined as shown in Fig. 1 and 2d in order to obtain the probability. The probability map is computed because the tumor affected seed is proportional to its distance normalized to the neighboring background seed. Hence this prefers the tumor seeds that are having higher probability and its distance to the background seeds is high and vice versa:

$$P_{Tr} = \ln(Z_{Bg}) / (\ln(z_{Bg}) + \ln(z_{Tr})) \quad (1)$$

Subsequent to this process, the obtained surface is smoothed with the intention of obtaining acute tumor

volume. For the smoothing process the level set algorithm is applied. This algorithm defines acute shape and for smoothing process. In general let $\Gamma(v, t)$ be the level set function, v be the position vector and t be the time of the level set evolution and initially the evolving surface is set to zero value that is $\Gamma(v, t) = 0$. The segmentation is obtained once the RMS difference between $\Gamma(v, t) = 0$ and $\Gamma(v, t - 1) = 0$ is less than a predefined minimum RMS value.

For this aforesaid process, the obtained surface is initialized which is considered both the inside and outside region of the surface sf . The vital idea of the level set surface is to represent the evolving contour by means of a signed function and its zero level is corresponded to the actual contour or outline of the tumor surface. The level set embedding is done over the tumor surface via the following equation:

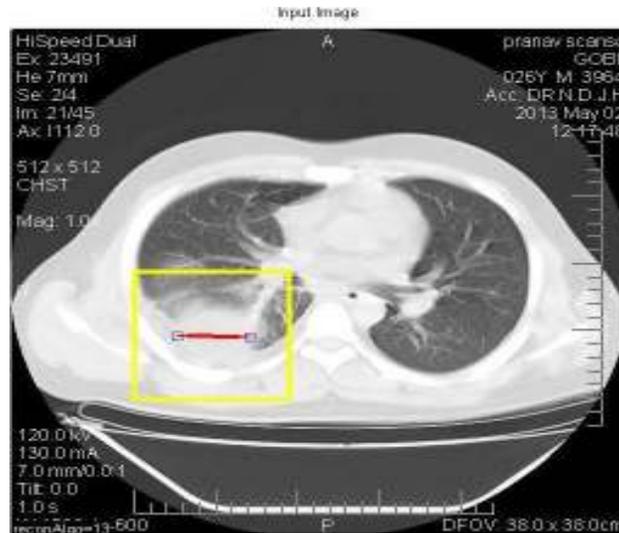
$$\frac{\partial sf}{\partial t} = (c - d)(c + d - 2Ptr)N \quad (2)$$

Here c and d are the inside and outside surface's means and N is the unit normal vector to surface sf . The level set function's zero level set indicates an initial estimation of the tumor surface sf and its developed on P_{Tr} with a piecewise constant region, though by exploiting a local Gaussian kernel to describe the inner and outer regions around the growing surface for estimating the regional statistics of the map. Once the surface's growth converges, then the final segmented tumor is attained.

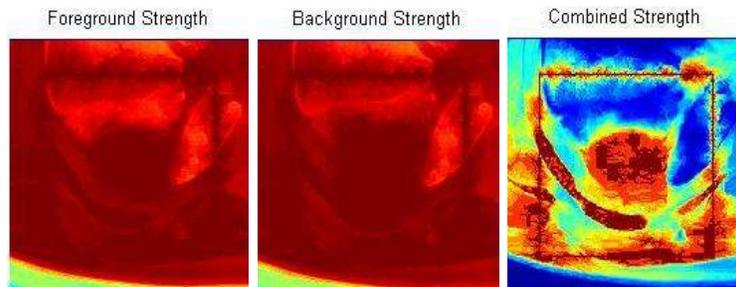
RESULTS AND DISCUSSION

The proposed lung segmentation process was implemented with the aid of the working platform of MATLAB ((version 7.12). The proposed system was examined by means of the publicly available lung images Fig. 1 and 2a. With the selected pixels as initial seeds, the CA algorithm was applied on the image for obtaining the foreground pixels i.e., here tumor pixels and background pixels as shown in Fig. 1 and 2b and c. In this algorithm, the threshold value (0.5) was utilized for the CA algorithm. The obtained output segments are given as input to the level set algorithm for extracting the apt tumor segment as shown in Fig. 1 and 2e. The stepwise output of the input image is depicted below.

The above two images depict the input image and then the image was applied with the CA algorithm and their outcomes background strength were shown above. Once the level set algorithm was applied the acute tumor segment was obtained as in Fig. 1 and 2f. The following Table 1 and Fig. 3 to 6 show the epsilon value and the spatial overlap of both the algorithms (Table 2).



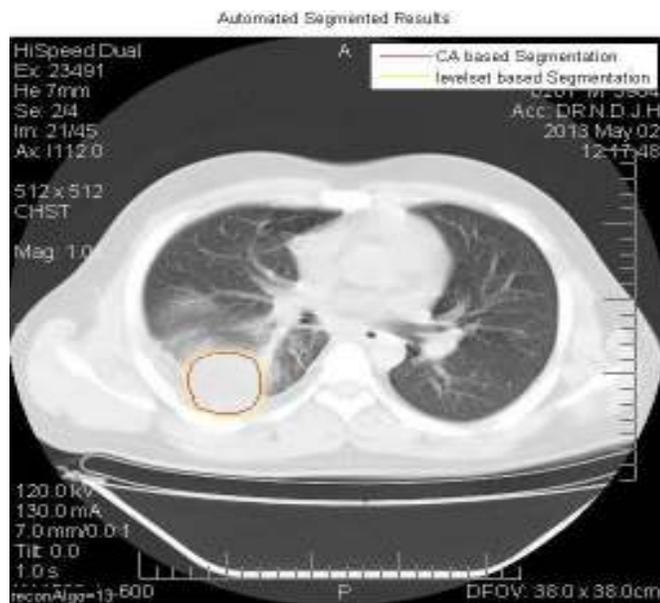
(a)



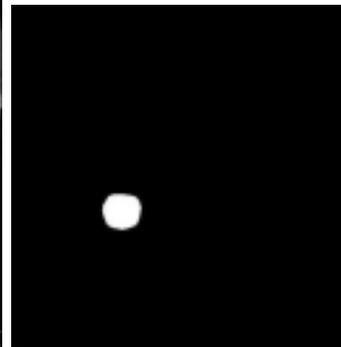
(b)

(c)

(d)



(e)



(f)

Fig. 2: (a) Input lung image 2, (b) foreground strength of input image 2, (c) background strength of image 2, (d) combined strength of image 2, (e) segmented tumor of image 2 segmentation using CA (red), segmentation using level set (yellow), (f) segmented tumor segment of image 2

Table 1: Parameters of CA algorithm and level set algorithm

Image number	Parameters of CA based algorithm coefficient of similarity		Parameters of level set algorithm coefficient of similarity	
	Epsilon	Spatial overlap	Epsilon	Spatial overlap
Image 1	0.8600	0.9219	0.8354	0.9065
Image 2	0.9940	0.8908	0.7931	0.8614
Image 3	0.9371	0.9426	0.9236	0.9603
Image 4	0.9951	0.9434	0.9785	0.9332

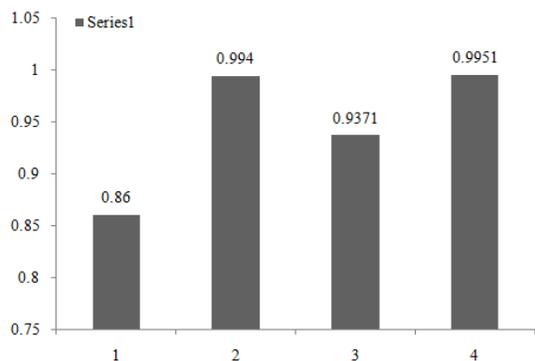


Fig. 3: Chart of epsilon parameter of CA algorithm

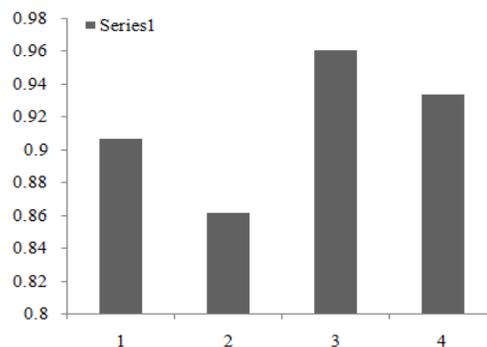


Fig. 6: Chart of spatial overlap parameter of level set algorithm

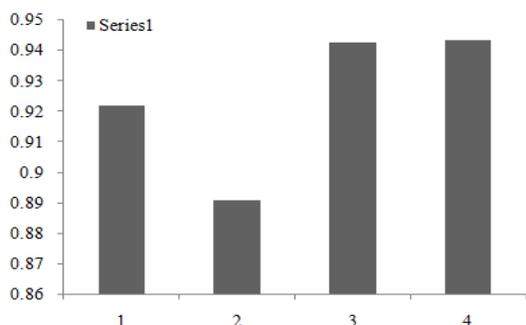


Fig. 4: Chart of spatial overlap for the CA algorithm

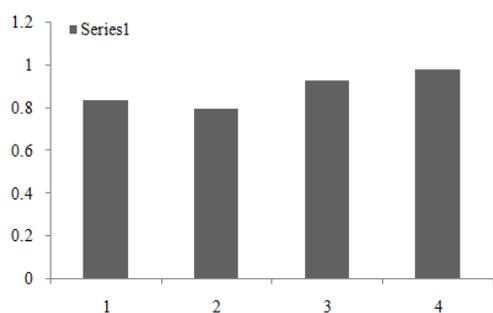


Fig. 5: Chart of epsilon parameter for the level set algorithm

True Positive (TP): Tumor sector is correctly segmented as tumor segment.

True Negative (TN): Non tumor sector is segmented as non tumor segment.

False Positive (FP): Non tumor sector is segmented as tumor segment.

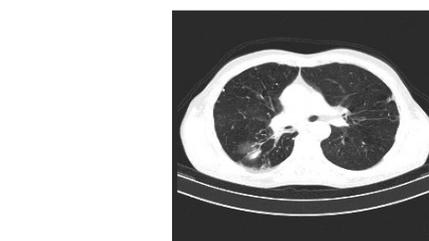


Fig. 7: Input image

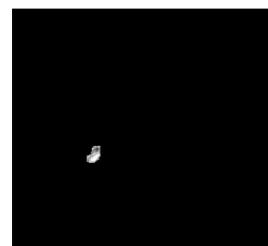


Fig. 8: Segmented tumor using region grow

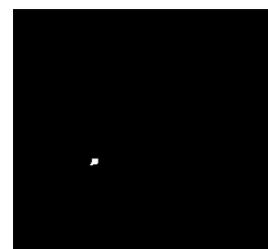


Fig. 9: Segmented tumor using level set algorithm

False negative: Tumor sector is incorrectly segmented as non tumor segment:

Table 2: Performance analysis

Images	TP	TN	FP	FN	Sensitivity	FPR	Accuracy	Specificity	PPV	NPV	FDR	MCC
Image 1	2	4	0	0	100	0	100	100	100	100	0	57.73503
Image 2	2	3	1	0	100	25	83.33333	75	66.66667	100	33.33333	54.77226
Image 3	1	4	0	1	50	0	83.33333	100	100	80	0	28.28427

Table 3: Compared analysis of region growing algorithm and our proposed method

Test image	Region growing cum level set		CA cum level set	
	Coefficient of similarity (€)	Spatial Overlap (SO)	Coefficient of similarity (€)	Spatial Overlap (SO)
Test image 1	0.4898	0.4455	0.8163	0.8090
Test image 2	0.2742	0.3792	0.9516	0.9764
Test image 3	0.4462	0.7789	0.9677	0.9788
Test image 4	0.5919	0.8119	0.9686	0.9431
Test image 5	0.6653	0.8392	0.9469	0.9686
Test image 6	0.3366	0.7509	0.9707	0.9653

Sensitivity

$$= \frac{\text{Number of True Positives}}{\text{Number of True Positives} + \text{Number of False Negatives}} \quad (3)$$

Specificity

$$= \frac{\text{Number of True Negatives}}{\text{Number of True Negatives} + \text{Number of False Positives}} \quad (4)$$

$$\text{False Positive Rate (FPR)} = \frac{FP}{N} = \frac{FP}{(FP + TN)} \quad (5)$$

$$\text{Positive Predictive Value (PPV)} = \frac{TP}{(TP + FP)} \quad (6)$$

$$\text{Negative Predictive Value (NPV)} = \frac{TN}{(TN + FN)} \quad (7)$$

$$\text{False Discovery Rate (FDR)} = \frac{FP}{(FP + TP)} \quad (8)$$

$$\text{Mathews Correlation Coefficient (MCC)} = \frac{(TP \cdot TN - FP \cdot FN)}{\sqrt{(TP + FN)(TN + FP)(TP + FP)(TN + FN)}} \quad (9)$$

Our proposed method is compared with the region growing algorithm and the following images Fig. 7 to 9 details the analysis. This shows that our proposed hybrid method acutely extract the tumor segment rather than the region growing algorithm.

This Table 3 details the compared analysis and that indicates the parameter obtained in the proposed method is quite better than the region growing algorithm in which the obtained results indicate the acute tumor segment.

CONCLUSION

In this study, the input lung image was applied with the multi-wavelet process and the denoised image was obtained. And then the CA algorithm was utilized for obtaining the seeds and for this process, the intensity and the mean of adjacent pixels was

considered. As a result of this process, the background and the foreground seeds (tumor seeds) were obtained. Consequently, the level set algorithm was applied to extract the acute tumor cells and the results have been showed in the result section. For the future work, the obtained output image will be utilized for the classification process of lung tumor.

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