Biomedical & Pharmacology Journal, December 2018. Vol. **11**(4), p. 2037-2042

Segmentation of Lung Images using Region based Neural Networks

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http://dx.doi.org/10.13005/bpj/1580

(Received: 15 September 2018; accepted: 02 November 2018)

In this article, a neural network-basedsegmentation approach for CT lung images was proposedusingthe combination of Neural Networks and region growing which combines the regions of different pixels. The proposed approachexpresses a method for segmenting the lung region from lung Computer Tomography (CT)images.This method is proposed to obtain an optimal segmented region.The first step begins by the process of finding the areawhich represents the lung region. In order to achieve this, the regions of all the pixel present in the entire image is grown. Second step is, thegrown region values are given as input to the Echo state neural networks inorder to obtain the segmented lung region. The proposed algorithm is trained and testedfor1,361CT lungslicesfor the process of evaluating segmentation accuracy. Anaverageof 98.50% is obtained as the segmentation accuracy for the inputlung CT images

Keywords: Image segmentation, Computed Tomography (CT), Lung images, Neural Networks.

Each pixel present in the segmented region is important for the process of image segmentation. This is common withsome features such as color based, intensity based, or texture based. Computer based segmentation of lung CT images has been an important and innovative development. Segmenting medical images continues to be a significant problem which is done by several researchers with in few decades. In general, medical image segmentation methods have various restrictions since the medical images are very similar in its gray level and texture. Due to this complexity, significant segmentation error may occur. Inorder to overcome the drawbacks present in it, a new neural network approach combined with clustering and region growing is proposed in this work.This new method can operate on high resolution medical images with low computational complexity.

Many methods such as thresholding based, knowledge based, edge detection, region growing, active contour/shape models and morphological based operations[3, 5-13] have been proposed by earlier researchersfor the process of segmenting the lung region of interest automatically in lung images more effectively.A new improved method for segmenting the regions of lung by combining a threshold-based and an adaptive based border marching methodwas proposed in[3]. Their modified algorithm process the smoothing operation in lung border in a way which is geometric in nature hence it can be used to include various forms of juxtapleural nature of nodules. This method can reduce the over segmentation done in abdomen regionwhich ispresent adjacent to the lung.They have analyzed their algorithm for 20 slices. Anunder-segmentation andover segmentation accuracy of 1.63 % and 0.43 %, respectively is obtained from their proposed methodology. The performance of threshold-based lung segmentation algorithms is given in[4] In this work, they have applied their proposed algorithm on a set of 276 chest CT scans which has a total number of 2292 slices. All the slices were taken under various abnormalities and under different scanning positions. Different threshold based lung segmentation schemes was applied and visually monitoredfor all the slices. An average error rate of 4.4 % was obtained in the total 126 scans.

Antonelli *et al*[5] proposed anew technique which combines traditional and purposely used image processing based methods, for example,segmentation based on thresholding, morphological based operations on opening and closing, detection of border its thinning and its reconstruction. And at last the region filling operation is also performed. The result is a binary image which is obtained fom a thresholding based technique. The morphological based operators such as opening and closing were applied for eliminating the smaller objects which is present inside the lung border. Lung borders are found using the tracking based algorithm. Operator called as morphological based thinning is applied for reducing the size of border size for the complete lung image which is used as input.The main drawback of their proposed method is the background cannot be eliminated completely when there is noise at the corners.

Arfan Jaffar *et al*[7]framed a new methodology for effective segmentation of the entire lung region from lung CT images. This can be achieved by combining the spatial based Fuzzy C-Means clustering and and morphological based techniques in an ordered manner. Removal of Background, Preprocessing, andoperation based on Morphological analysis is used for this effective segmentation. Abackground removal operator which is based histogramis used for removing the complete pixels which is present around the lung border. Preprocessing operation isdonein order to smoother and removing the unwanted noise present around the final segmented result. At last,operators based morphological computations are used for separating the edges around the lung for preforming the filling process around the small holes which is present in it.Leader *et al* in[11] developed aheuristic based methodology for effective segmentation of lung images. Here, they used a combination of slice and value of pixel threshold combined with two or more sets of rules for classification. Initially, image pre-processing methods are applied to remove the background pixels. A pixel based thresholding operation is done for finding the presence of tissues of lung area.

Refinement is the final step in which all the regions which are initially segmented is performed for pruningthe airways which were detected incorrectly. This process can also used to separate the right and left lungs from the overall CT lung image.The overall accuracy of their method was computedby using 101 CT cases which has91 thick slices and10 thin slices. They have obtained an overall segmentation accuracy of 94.0% for all the 2,969 thick and 97.6% accuracy for 1,161 thin CT slices.

Shiying *et al*[1] developed a novel method for identifying lungs in CT pulmonary slices. The complete methodology is partitioned in to three major categories. Initially,Gray-level thresholding has been used to extract lung from CT-Scanned image. Second step is the separation of left and right sides f lungs. This process can be done by identifying the junctions of anterior and posterior by using a dynamic programming. Finally,a sequence of morphological operations are used to smooth the irregular boundaries along the mediastinum. The major drawbacks of this algorithm are its fixed ball size and over segmentation.

Description of the Proposed Algorithm

Region growing (RG)[2] is a technique which identifies the sets of pixels which are connected and continuous in nature present in the image. This can be done using some threshold based operations. Region growing is an operation, which can be done by choosing a point of seed for growing the regions. This can be done by checking the availability for including the neighbouring pixels which is based on the threshold. Each set of pixels will become the seed for effective growing of adjacent pixels. This process can be performed throughout the complete image and it can be continued till all the entire pixels are included in the growing region of process. The complete process is applied in CT images for the process of segmentation. In this method, initially, a 3x3 pixel of lung region is taken for processing. The rule of inclusion [12] is applied in this method for fixing a value by selecting the pixels which has a value of intensity which is lower than the set threshold. The above said process is carried out on he complete images from the starting to ending pixels present in it.

ESNN Topology

Recurrent type discrete and time based neural network is the Echo State Neural Network[14]. It has an input unit of S, X as the reservoir of internalin terms of unitsoutput as Y in terms of units. It is a recurrent type neural network which has a reservoir which has a non-available trainable recurrent part and a readout which is simple and linear in nature. The weights that represents the connection and inputs are generated randomly.

The ESNN which is used in this algorithm has three layers. They are an input type layer, middle type layer and an output type layer. The various activation function of the input type layer, middle type layer and the output type layers at an interval of time t can be computed as follows.

$$Z_{S(d)} = (a_1(d) + a_2(d) + \ldots\ldots a_n(d)) \quad \ldots(1)$$

$$Z_{X(d)} = (b_1(d) + b_2(d) + \ldots\ldots b_n(d)) \quad \ldots(2)$$

$$Z_{Y(d)} = (c_1(d) + c_2(d) + \ldots\ldots c_n(d)) \quad \ldots(3)$$

The link betweenunits of input and the units of internal are expressed by an I x X weighted matrix which is represented by U. All the connections are accumulated in an Y × Y weighted matrix which is represented by W, and All the connections are accumulated for the units of internal in terms of output units are expressed in Y × X weighted matrix which is represented by V. The upgradation of input units is based on

$$I(d+1) = f(U\,a(d+1) + Y\,b(d)) \quad \ldots(4)$$

Where, f is the activation function of various reservoirs present in it. It is represented as a sigmoidal type function called tan h. The output units are upgradation of output units can be done based on

$$O(d+1) = f(Vc(d+1) + Y\,b(d)) \quad \ldots(5)$$

ESNN With RG Topology

The ESNN with RG topology consists of three layers such as layer 1, layer2 and layer 3. The layer 1 is the input layer ($Z_{S(d))}$. Layer 2 is the hidden layer ($Z_{X(d)}$) and layer 3 is the output layer ($Z_{Y(d)}$) which contains reservoirs (nodes). The recurrent type Echo State Network has various highly inter linked reservoirs with dynamical based components and states. These are called as echo states. One of the main memory less property of this neural network is its linear readout which can be trained for producing the desired output as result.The hidden layer receives the features from the CC algorithm. Each and every node that are present in the network between the input and the hidden layer are linked in such a way that the node that represent output from the layer of output is given or send back towards the hidden layer. When a pattern is presented for training the proposed ESNN with RG, a state vector is generated in the layer which has hidden structure. Similarly, n number of state vectors is formed for n number of patternsrespectively. These state vectors represent the condition of the pattern.

Working Principle of ESNN with RG

The ESNN is trained with training patterns obtained from the RG for getting the final resultants as weights. During the process of testing the proposed neural network, a set of pixels as pattern from the complete window which is in moving state is accessed and processedwhich has the trained weights in predefined form for getting an output in the layer that is meant for output of the neural network. Training and testing procedures of the proposed neural network is as follows.

Training and Testing ESNN with RG

The training patterns formed through the RG algorithm are further fed as input towards the Neural Network to train it along with ESNN. For segmenting the image effectively, three main window features are used in the layer that is used for input. Its output and the corresponding target outputs (0.1 or 0.9) are presented in the output layer of the proposed neural network topology called as ESNN. A new state vector is formed by giving the summed value over an activation function which is the tan h function. The obtained matrix is rectangular in type.

Algorithm for Training

Step 1: RG as Input features

Step 2: Fix the total set of applicable reservoirs.

Step 3: Fix the total set of nodes towards input layer as three.

Step 4: Fix the set of nodes towards output layer as set of values assigned in target.

Step 5: Fix the set of state vector and set of reservoirs as zero.

Step 6: Fix theweights of random which is common to input layer ($Z_{S(d)}$) and hidden layer ($W_{X(t)}$). Set the initial weights in output layer as ($Z_{Y(d)}$) and hidden layer as ($Z_{X(d)}$).

Also Set the weights for reservoirs.

Step 7: Compute the state$_{_next}$vector = tanh (($Z_{S(d)} Z_{X(d)})_{weights}$ *Input$_{_pattern}$ + $(Z_{X(t)})_{\_weights}$ * state$_{_present}$ vector+ $(Z_{X(d)}\ Z_{Y(d)})_{\_weights}$ * Target$_{_pattern}$).
Step 8: Compute, A = Pseudo_inverse (State_$_{allpatterns}$vector).
Step 8: Compute, $Z_{\_out}$ = A * T
Step 9: Store $Z_{\_out}$ as segmented output.

Algorithm for Testing or segmenting the image

Step 1: RG as Input features
Step 2: Fix the total set of applicable reservoirs.
Step 3: Compute thestate_vector = tanh ($Z_{a(d)} Z_{b(d)})_{\_weights}$ *Input$_{_pattern}$ + $(Z_{b(d)})_{\_weights}$ * state_$_{present}$vector+ $(Z_{b(d)}Z_{c(d)})_{_weights}$xTarget$_{_pattern}$).
Step 4: Approximate output = state_vectorx$Z_{_out}$.
Step 5: Allot 0 for black and 255 for white in the new column of matrix which is the segmented result.

RESULTS AND DISCUSSION

In this section, we the results of the proposed methodology is presented. Computing the segmentation accuracy is the most commonly usedmethod to ensure the performance of segmentation Segmentation accuracy[2] $A_{prop}$is computed as follows

$$A_{prop}=S_{prop}/O_{prop} \times 100 \quad ...(6)$$

$$S_{prop}=(Solidity+Area+Perimeter_{segmented}) \quad ...(7)$$

Table 1. Segmentation Results for Different Images using proposed methodology

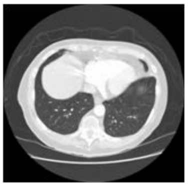
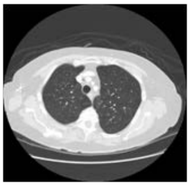
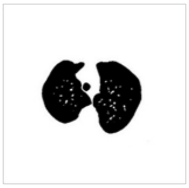
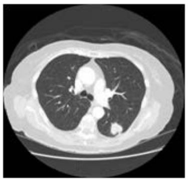
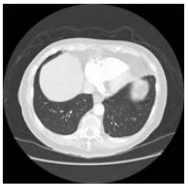
No	Original image	Region growing	Segmented Result
1.			
2.			
3.			
4.			
5.			

Table 2. Segmentation Accuracy based on Number of objects

Image		Solidity	Area	Perimeter	Total	A_{prop}
Image 1	Segmented	153.8936	1527	626.3849	2528.3044	98.98
	Unsegmented	170.8582	1545	638.3848	2554.2435	
Image 2	Segmented	132.5644	1439	867.1724	2528.7368	98.43
	Unsegmented	135.5644	1509	924.42	2568.9844	
Image 3	Segmented	170.875	1204	886.2178	2311.0928	98.35
	Unsegmented	175.876	1252	921.7996	2349.6756	
Image 4	Segmented	180.809	979	830.7306	2232.2680	98.32
	Unsegmented	190.701	1039	880.71	2270.4110	
Image 5	Segmented	182.5944	1439	867.1724	2528.7368	98.43
	Unsegmented	135.5644	1509	924.442	2569.0064	
					Average:	98.50

$$O_{prop}=(Solidity+Area+Perimeter_{unsegmented}) \quad ...(8)$$

where S_{prop} and O_{prop} are the region properties.

The segmented images shown in Table 1 are obtained with optimum values of Threshold =140 for block size 3x3 for different images. In this approach, the region grown images are considered as ground truth image. Table 2 shows the segmentation accuracy based on the number of objects for all the five sample CT lung slices. The performance remains closely consistent which indicates the value of the variables of ESNN with CCR algorithm are optimal. From this table, it can be observed that our proposed segmentation method provides an overall accuracy of 98.50% in segmenting the CT lung images effectively

CONCLUSION

In this paper, a new neural network approach based on the combination of region growing method and Neural Networks has been proposed to segment the lung CT images effectively. This method overcomes the disadvantages of existing techniques since it deals with the pixels present in the entire image. In this method, a combination of clustering along with region growing is used for entire area of the gray scale image. Hence, more clarity is obtained in segmenting the region of interest present in the image. The proposed algorithm is trained and tested for 1,361 different lung CT slices In order to measure the performance of the proposed method. The major contribution of this paper is an improvement in segmentation accuracy by combining neural network along with the clustering and region growing. Future works in this direction can be the proposal of a new methodology for finding the presence of nodules and to analyze the time complexity for different CT lung images.

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