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Automated Segmentation of Optical Nerves by Neural Network based Region Growing

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ABSTRACT
Computer Aided Diagnosis (CAD) of retinal image has been a revolutionary step in the early diagnosis of diseases present in the eye. Developing an efficient and robust algorithm for optical nerve segmentation has been a demanding area of growing research of interest during the last two decades. The initial step in computer aided diagnosis of retinal image is generally to segment the nerves present in it and then to analyze each area separately in order to find the presence of pathologies present in it. This research reports on segmentation of the nerves by segmenting the retinal images using Echo State Neural Networks along with the combination of region growing algorithm. Region growing has been combined with ESNN in this work since it reduces the number of steps in segmentation for the process of identifying a tissue in the CT retinal image. The performance of this proposed segmentation is proved to be better when it is compared with other existing conventional segmentation algorithms. From the experimental results, it has been observed that the proposed segmentation approach provides better segmentation accuracy.

Keywords
Contextual clustering, Segmentation Algorithm, Retinal image.

1. INTRODUCTION
Segmentation methods are useful for partitioning an image into multiple segments inorder to provide an effective representation of the objects present in it. Moreover, Image segmentation is also useful for locating objects and boundaries (lines, curves, etc.) and to assign a label to every pixel in an image such that pixels with the same label share certain visual characteristics. Moreover, each of the pixels from particular regions are similar with respect to some characteristic or computed property, such as color, intensity, or texture. At the same time, the adjacent regions are significantly different with respect to the same characteristic [5].

The various regions obtained by segmenting an image can be further used for different types of analysis and interpretations. Therefore, segmentation of image involves extracting important features and deriving the relevant metrics to segregate regions of homogeneous intensities. In order to achieve this, it is necessary to choose a selective region of interest by considering the application requirements. In the past, many image segmentation methods have been proposed by various researchers for performing successive image analysis. In addition, many researchers have used the existing thresholding techniques for segmenting the various regions of interest. In short, the most frequently used techniques for segmentation are statistical methods, geometrical, structural, model based, signal processing methods, spatial domain filters, Fourier domain filtering, Gabor and wavelet models have also been used in most works present in the literature [6, 7].

In this paper, the combination of ESNN along with the region growing algorithm have been used for effective segmentation of the CT retinal image.

The remainder of this paper is organized as follows: Section 2 discusses the features and methods proposed in related works. Section 3 explains the problem definition obtained in this research work and highlights the advantages of segmenting retinal CT images. Section 4 provides the results. Section 5 gives the conclusion on this work and also provides some possible future works.

2. RELATED WORKS
Accurately segmentation should be done since, the pathologies present on it may be on the boundary of the retina. Such pathologies will be lost and it reduces the detection accuracy, if the entire retinal area is not segmented accurately. Main goal of retinal region of interest segmentation is to separating the nerves corresponding to pathology region from the voxels corresponding to the surrounding anatomy

Many techniques have been employed to the exudate detection. Gardner et al. [8] proposed an automatic detection of diabetic retinopathy using an artificial neural network. The exudates are identified from grey level images. The fundus image was analyzed using a back propagation neural network. The technique did not work well on low contrast images.

The thresholding and RRGS technique were widely used. Sinthanayothin et al. [5] reported the result of an automated detection of diabetic retinopathy on digital fundus images by RRGS algorithm where the performance was measured on 10×10 patches rather on the whole image. Usher et al. [7] detected the candidate exudates region by using a combination of RRGS and adaptive intensity thresholding. The candidate regions were extracted and used as input to a neural network. Poor quality images affected the separation result of bright and dark lesions using thresholding and exudate feature extraction using RRGS algorithm.

Zheng et al. [9] detected exudates using thresholding and a region growing algorithm. The fundus photographs were taken with a non-mydriatic fundus camera and were then scanned by a flat-bed scanner. Colour normalization and local contrast enhancement followed by fuzzy C-means clustering and neural networks were used by Osareh et al. [10]. The system works well only on Luv colour space but in the case of non-uniform illumination the detection accuracy is low. Mitra et al. [11] applied naïve Bayes classifier for diagnosis of diseases from retinal image. A system can provide a good decision support to ophthalmologist.

3. ESNN WITH REGION GROWING

Region growing (RG) [1] is an iterative technique employed to identify connected regions of interest (contiguous sets of voxels) in images, obeying some inclusion rule (generally based on threshold values), and according to the notion of discrete connectivity [2]. Initially, the region growing starts by choosing an initial pixel as a seed point which is present in the region to be grown and, after checking its inclusion of neighbors in the growing region based on the threshold value. Each included voxel becomes in turn a seed point for the following iteration. The above process continues until all the pixels are added in the grown region based on the set of rules and threshold.

In our approach, a region growing approach along with the clustering is used to fix the threshold inorder to segment the region of interest present in the CT retinal images. The initial seed point is a voxel (3x3 or 5x5 pixels) belonging to the retinal nerve region, and the fuzzy rule fixes a value by selecting the voxels with intensity values lower than the given threshold. In this way the entire nerve is connected which present in the image is starting from the bronchi, carena, and the trachea. The initial seed point is automatically chosen by selecting the 3x3 pixel which is present in the central slice of the CT image and grows towards the entire region present in the image.

Recently, there has been considerable interest among researchers in statistical clustering techniques [3] in image segmentation. In a clustering technique along with the region growing, each pixel is associated with one of the finite number of threshold is grown to form disjoint regions. The contextual clustering method proposed by [4, 9] is a supervised algorithm. It uses a 3 X 3 overlapping windows of pixels to form a segmented image. The quality of segmented image depends upon 1) A defined threshold value (T=140) by the user which is used to choose the nearest regions for segmentation, 2) a controlling parameter β which is in the range of 0< β <1, 3) the median value of the 9 pixels in the window, 4) the total number of intensity values (u) >1 inside the window, excluding the already identified median value.

3.1 Echo state neural network

Segmentation of the CT image has been done with Echo state neural network [3]. ESNN is a recurrent neural network which contains at least one cyclic path, where the same input information repeatedly influences the activity of neurons on the cyclic path. Such networks are more closely related to biological neural networks, which are also mostly recurrent. The outputs of this internal PEs (echo states) are fed to a memory less but adaptive readout network that produces the network output. The interesting property of ESNN is that only the memory less readout is trained, whereas the recurrent topology has fixed connection weights. This reduces the complexity of RNN training to simple linear regression while preserving a recurrent topology, but obviously places important constraints in the overall architecture that have not yet been fully studied.

The echo state condition is defined in terms of the spectral radius (the largest among the absolute values of the eigenvalues of a matrix, denoted by (|| ||) of the reservoir's weight matrix (|| W || < 1). This condition states that the dynamics of the ESNN is uniquely controlled by the input, and the effect of the initial states vanishes. The current design of ESNN parameters relies on the selection of spectral radius. There are many possible weight matrices with the same spectral radius, and unfortunately they do not perform at the same level of mean square error (MSE) for functional approximation.

The recurrent network is a reservoir of highly interconnected dynamical components, states of which are called echo states. The memory less linear readout is trained to produce the output. Consider the recurrent discrete-time neural network with M input units, N internal PEs, and L output units. The value of the input unit at time n is $u(n) = [u_1(n), u_2(n), . . . , u_M(n)]^T$,

The internal units are $x(n) = [x_1(n), x_2(n), . . . , x_N(n)]^T$, and

Output units are $y(n) = [y_1(n), y_2(n), . . . , y_L (n)]^T$.

The connection weights are given

- in an (N x M) weight matrix $W^{back} = W_{ij}^{back}$ for connections between the input and the internal PEs,
- in an N × N matrix $W^{in} = W_{ij}^{in}$ for connections between the internal PEs
- in an L × N matrix $W^{out} = W_{ij}^{out}$ for connections from PEs to the output units and
- In an N × L matrix $W^{back} = W_{ij}^{back}$ for the connections that project back from the output to the internal PEs.

The activation of the internal PEs (echo state) is updated according to

$x(n + 1) = f(W^{in} u(n + 1) + Wx(n) +W^{back}y(n))$,

Where $f = (f_1, f_2, . . . , f_N)$ are the internal PEs' activation functions.

Here, all f_i's are hyperbolic tangent functions $\frac{e^x - e^{-x}}{e^x + e^{-x}}$. The output from the readout network is computed according to $y(n + 1) = f^{out}(W^{out}x(n + 1))$, .

Where $f^{out} = (f_1^{out}, f_2^{out},...., f_L^{out})$ are the output unit's nonlinear functions. Generally, the readout is linear so f^{out} is identity [14].

ESNN algorithm consists of two phases namely Training and Testing (segmentation)

Phase 1: Training ESNN

Step 1: Read 31st slice in DICOM format and separate the image into 3 x 3 overlapping blocks of pixels.

Step 2: Decide the number of reservoirs.

Step 3: Decide the number of nodes in the input layer = 3.

Step 4: Decide the number of nodes in the output layer = number of target values=1.

Step 5: Initialize state vector (number of reservoirs)=0.

Step 6: Initialize random weights between input layer (I_L) and hidden layer(h_L). Initialize weights between output layer(o_L) and hidden layer (h_L). Initialize weights in the reservoirs.

Step 7: Calculate state_vector$_{next}$ = tanh $((I_L h_L)_{weights}$*Input$_{pattern}$ +$(h_L)_{weights}$* state vector$_{present}$+$(h_L o_L)_{weights}$ * Target$_{pattern}$).

Step 8: Calculate, a = Pseudo inverse (State vector $_{all\ patterns}$).

Step 9: Calculate, W_{out} = a * T and store W_{out} for segmentation.

Phase II: Testing (Segmentation)

Step 1: Adopt step 1 and step 2 mentioned in Training.

Step 2: Calculate state_vector= tanh $((I_L h_L)_{weights}$*Input$_{pattern}$ +$(h_L)_{weights}$* state vector$_{present}$+$(h_L o_L)_{weights}$ * Target$_{pattern}$).

Step 3: Estimated output= state_vector * W_{out}

Step 4: Assign 0 (black) or 255(white) in the new matrix which will be the segmented image.

4. EXPERIMENTAL RESULTS AND DISCUSSION

Retina images have been considered in this paper. Computed tomography images of different patients have been taken from the Drive database. The ESNN segmented results for different region growing threshold along with its original images has been presented in Table 1

Table 1 Segmented Results of Block Size 3x3

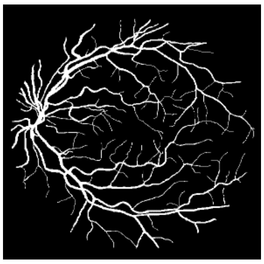
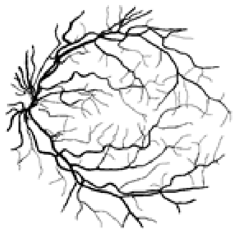
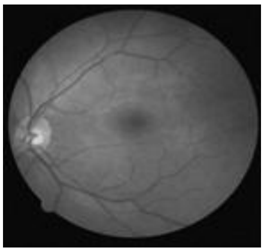
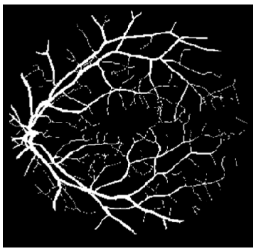
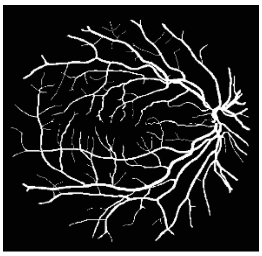
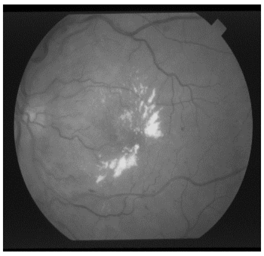
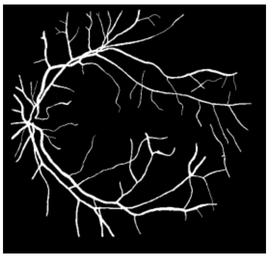
No	Original Image	Ground Truth	Segmented Result
1			
2			
3			
4			

Table 1 shows the segmented images obtained from the original retina image. The parameters given for the variables of ESNN algorithm are block size of the moving window is 3x3.

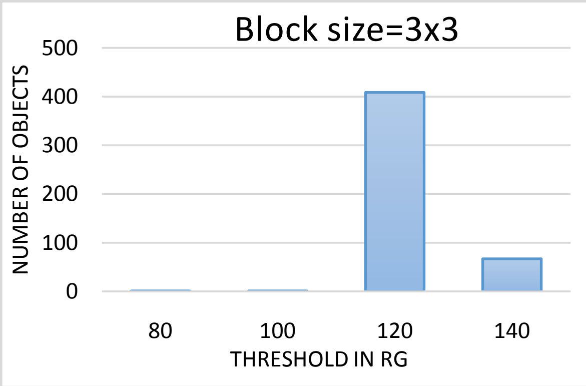


Figure 1 Segmented Objects for Different Threshold at Block Size 3x 3

Figure 1 shows the number of objects calculated using region properties of Matlab for a block size of 3x3 moving window.. More number of segmented objects is present when the image grown to a threshold of 120 for region growing. Only one object is obtained when the threshold is less than 120. Correct number of objects that is 67 is obtained when the threshold is 140.

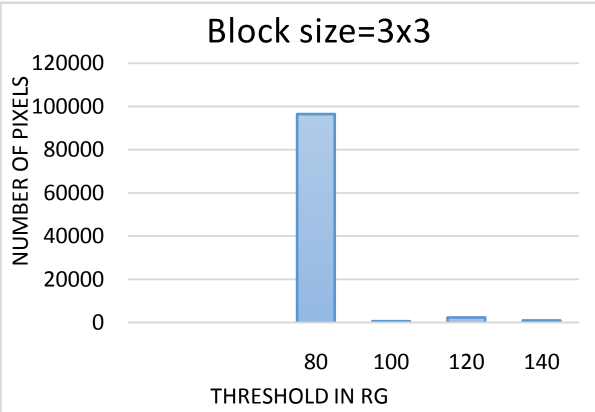


Figure 2 Segmented Pixels for Different Threshold at Block Size 3x 3

Figure 2 shows the number of pixels calculated using region properties of Matlab for a block size of 3x3 moving window. More number of segmented pixels is present when the image is segmented with threshold less than 100. All the segmented pixels correspond to one object only. Keeping the ground truth image into consideration, the number of pixels corresponding 67 objects are found to be the correct number of segmented pixels (999). Matlab 'Region props' function has been used and the number pixels and number of objects are shown in figure 1 and 2. Earlier researchers had used different metrics to evaluate the segmentation accuracy. In this report, we have used the 'Region props' function to evaluate the accuracy of segmentation and it has been found that the proposed segmentation approach is much better when compared to that of remaining segmentation approaches mentioned in the literature.

5. CONCLUSION

In this paper we have proposed a new method for segmenting retina images using the supervised contextual clustering based region growing method. The main purpose of proposing this approach is to improve the segmentation accuracy by reducing the false segmentation. Main features of the proposed algorithm is the use of region growing along with the Echo State Neural network. This method is applied to different types of retina datasets inorder to validate the efficiency of the proposed algorithm. In this proposed framework, segmentation of the normal tissues is not degraded since the unwanted section other than the region of interest is removes exactly.

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