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A Robust Deep Net Method for Retinal Image Segmentation

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Abstract: Segmentation of retinal blood vessel nowadays is one of the critical factors that determine the performance of a CAD based system. Segmentation means extracting the region of disease from the image. Segmentation of retinal blood vessels' boundary is required to segment them precisely because an eye surgeon wouldn't be able to predict the disease area if segmentaion not accurately done. Segmentation in the proposed method is carried out by Morphological operation that extracted the feature robustly and ultimately distance based clustering is applied to segment the image.

Keywords: Segmentation, Clustering, Morphological, PSNR, MSE, Accuracy.

Introduction

Artificial neural network with over two hidden layers are referred to as a deep neural network. There are different architectures of deep neural networks depending on types of connections between layers or operations within a layer or types of units within a layer. For a multi-layer perceptron, there are feed-forward connections whereas a Recurrent Neural Network contains recurrent connections that give past signals to process along with the present signal during training. A Convolutional Neural Network consists of convolution layers that perform Convolution between input data and a sequence of feature detectors. A Deep Belief Net consists of stochastic units and there are connections between layers from top layer to bottom layer.

These models have been used to tackle a variety of problems ranging from image analysis to natural language processing. Deep learning has proved very effective in image segmentation, with very robust applications of object, human or semantic segmentation to natural images [1]. So far, organ segmentation from medical images has seen relatively limited work, including brain part segmentation from MRI images and cell segmentation from microscopic images [2], [3]. Applications of deep networks to retinal vessel segmentation have also begun to emerge over the past few years [3]–[9]. A major strength of employing a deep network in medical image segmentation can be the adaptation of the technique to segment new data, obtained by a new acquisition system, by simply retuning the network. By way of contrast, classical techniques have to undergo adaptation to segment new data, frequently involving redesigning following the new dataset or trying to find optimal parameters. On the negative side, training a deep network can prove to be a problem of acquiring large sets of labeled examples, and that can be regarded as the greatest drawback of this technique.

Proposed Method

In this work, cross-modality learning method is considered to segment the vessels based on the fact that it takes into consideration the cohesion of neighbor pixels belonging to a similar class in the process of segmentation. Further, the method applies to the nature of the problem elucidated hereinafter. The fundus image patches can be regarded as noisy versions of the vessel masks. It is illustrated through a fundus image patch and its potential vessel mask in Figure 1.

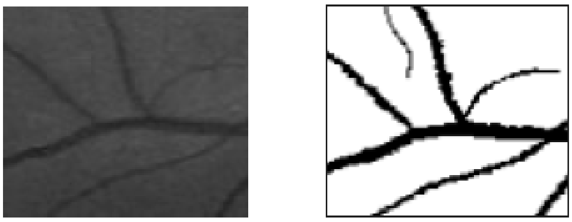

Figure 1 A fundus image patch in the left and its vessel map in the right

As illustrated from the figure, the correspondence between these patches of fundus images and their corresponding vessel masks is not that complicated, compared to the correspondence between the samples of audio and visual data in earlier applications of cross-modality learning [10]. It is possible to have a linear correspondence between fundus images and their vessel map in the case of unrealistically low noise levels, nearly zero, in fundus images. Due to this likeness, a joint representation learned among fundus images and their vessel masks can respond to the properties of the two data modalities by emphasizing the central structures of concern, blood vessels, concurrently [11]. Application of this method can be done by a generative learning process, for example by employing a generative morphological operation. There are two explanations of why a generative learning method is chosen. The first reason is that both cross-modality learning and generative learning need a proper representation of the input. The second reason is that the learned feature from the generative training of a DBN, also known as pre-training, can be manipulated to gain helpful feature in the context of cross-modality learning [12].

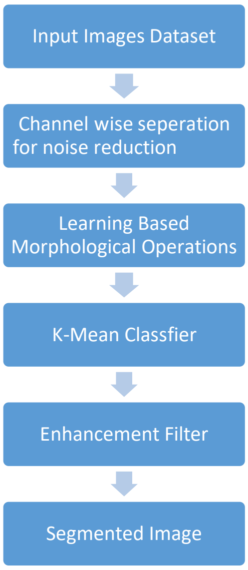

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Figure 2 Proposed Method

Morphological operations assist in smoothen the images and extract the feature from the image. The feature extraction is carried out to maintain the original and the actual expected shape of the retinal blood vessel. The different operations are employed like dilation and erosion operations are employed combinations to execute the edges detection after the threshold is predicted dynamically. The dilation process is applied to isolate the pixels from one another. For all the clip window similar pixels the 1's matrix is created and none of them is created like matrix of 0's by which the boundaries can be predicated. The process of erosion will eliminate the redundant boundary pixels to left user with clear idea of the boundary and dimensions. The quality of the image will be measured based on the MSE and PSNR. The MSE is mean square error which is calculated after subtracting the final image from original [2], [13], [14]. The PSNR value is calculated by:

$$PSNR = 10\log_{10} [I^2 / MSE] \text{ …….. (1)}$$

where I ranges from 0 to 255.

Results and Discussion

The proposed network's performance is tested on the CLINICAL dataset. The proposed method's segmentation performance will first be inspected on the best case and the worst case images, and then compared to that of the state of the art techniques.

Table I represents the overall performance of the network proposed by us on the CLINICAL dataset with regards to evaluation parameters. It also reflects the best and the worst performances based on the highest and lowest accuracies. As seen from the Table, there is not that large a difference between best case and worst case performance metrics based on accuracy. The proposed network achieved its best and the worst performances respectively on the 19th and the 3rd images. These images also correspond to the best and the worst performances of recent studies employing supervised algorithms [7], [15], [16]. The average threshold value in binearization of these vessel probability maps emerged to be 0:1305_0:0432 (mean _standard deviation). Simulated vessel probability maps and binary vessel maps of these images may be obtained by visual observation from Figure 3.

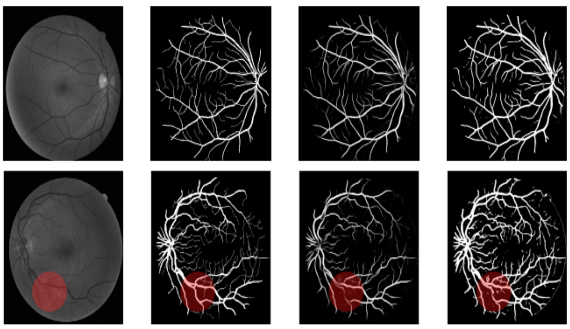

Figure 3 Channel wise Segmentation

In Figure3, optic disc discrimination from blood vessels in both best and worst case binary maps is done well, notwithstanding the resemblance of its border to blood vessels in terms of levels of contrast. Again, in cases of uniform illumination over fundus images and poor blood vessel contrast, there also does not appear to be any disruption of even small blood vessels detection. Conversely, the proposed network appears to be at times deceived by pathologies in fundus images and can at times treat them as part of blood vessels. This can be appreciated by the red circular area in the binary vessel map of the worst case in the same figure. The proposed network was also found to errantly treat a portion of cotton wool spots. Though these responses are weaker than or nearly equal to the responses of neighborhood capillaries in the corresponding probability map, some pathologic responses appear in the end binary map due to extremely low threshold. Also, readers must keep in mind that the CLINICAL dataset predominantly has healthy fundus images, so it could also be a contributor to network's poor performance over pathologic images. The proposed network's performance generated bigger AUC value, outperforming the performances of the state of the art deep network proposals [3], [17]–[19]. For the rest of the evaluation measures, the proposed method's performance compares favorably to the performances of the earlier methods. Among them, Author in [20] comes closer to the proposed method: both employed a cross-modality learning strategy in vasculature segmentation, and also employed fully connected networks. But how the methods are trained differ. In proposed network weights in each layer are initialized with weights learned with the probabilistic training of RBMs. However, Li et al.'s network is a standard fully connected network with modification, where the first layer of their network is initialized by the weights learned by training a de-noising auto encoder. The rest of the second and third layers were initialized by sampling from a normal. In addition, the number of hidden layers employed in the networks varies.

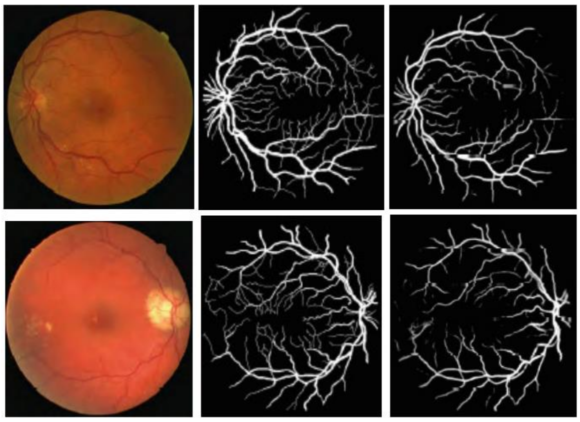

Figure 4 Blood vessels segmentation from ground truth image

Table I Best, average and worst performance of segmentation using proposed method on clinical dataset

	AUC	Accuracy	Sensitivity	Specificity
Mean	0.98%	0.93%	0.78%	0.98%
Max	0.98%	0.96%	0.79%	0.98%
Min	0.97%	0.94%	0.74%	0.97%

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Table II PSNR Values of proposed and existing methods

Method	PSNR Value
DUNET [21]	31
Median and CLAHE [22]	33
Distance [23]	32
Clustering [24]	29
Proposed Method	52

Conclusion

In recent times, deep learning methods have shown better performances than other methods [33]. As a consequence, I employ a deep network to segment vasculature. While the overall trend in vasculature segmentation is to classify each pixel in a fundus image into a vessel pixel and a non-vessel pixel, consideration of spatial connectivity of label pixels in network output has been seen to enhance the quality of segmentations [36]. The spatial connectivity of label pixels is in consideration in this thesis by producing vessel masks of input image patches upon being compliant to the cross-modality learning method. To make the feature extraction of the proposed more spatially connected, the proposed feature extraction is improved using a de-noising, which was found to yield more at probability responses to vasculature to image background. While the impact of this is not to be regarded as an improvement in terms of segmentation where over a threshold probabilities are tagged the same class, the same impact can prove to be beneficial to the robustness of the proposed tracking method.

The upgraded segmentation is also found to be adaptable to a range of applications by making minimal changes to its architecture and not altering significantly the method of network training. The network performed equally or better on the low resolution image segmentation when applied directly, compared to similar techniques.

Table III Performance of Segmentation on used Clinical Dataset

Category	Accuracy
Matched [25]	94.84%
Filter [24]	93.41%
Adaptive [13]	93.79%
Multiscale [26]	92.90%
Pattern classification [25]	94.79%

Filter Based Method [27]	95.28%
Image Features Based [28]	94.88%
Proposed Method	98.15%

Conclusion

Day by day, the number of patients and the requirement of the vessel segmentation are rising. The reason is to precisely segment the disease boundaries to act and treat the patient accordingly. The blood vessels are segmented by the RGB segmentation first and converting the image into grey scale. The images are processed by the morphological operations to isolate the features by which our proposed methodology will segment the retinal blood vessels precisely. The clustering based on distance is employed to categorize the pixels based on the location, area and intensity to assign each pixel to the proper cluster. The proposed methodology has demonstrated the precision of greater than 98% and the images are improved as the PSNR value greater than 50. The proposed methodology is effective in comparison to several available algorithms. The authors can categorize the images based on the segmented retinal blood vessels images in the future.

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