# BLOOD VESSEL FEATURE SEGMENTATION TO RETINAL IMAGES BASED ON ACTIVE CONTOUR MODEL WITH HYBRID REGION INFORMATION

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**Abstract —** *Computerized detection of blood vessel structures is becoming of interesting part in the field of the diagnosis of the vascular diseases. In this paper, a novel filter kernel function with Cauchy distribution is used to improve the accuracy of the automated retinal vessel detection. Moreover, for good segmentation performance, the proposed model takes the benefits of using distinct types of region information. We evaluate our proposed model performance by using first order parameters and also second order parameters like sensitivity, specificity and accuracy by comparing with the existing models.*

***Keywords:*** Cauchy PDF, retinal images, vessel, segmentation, active contour.

## 1.Introduction

Vascular system is the body's network of blood vessels. It consists of the arteries, veins and capillaries that carry blood to and from the heart. Vascular diseases are the challenging issues in the present society. Therefore the detection and analysis of the blood vessels in medical images is a primary task in much clinical application to support early detection, diagnosis and optimal treatment. Blood vessels seem to be linear structures disturbed at different orientations and scales in an image. Segmentation is needed for the analysis of these blood vessels at different angles. So, various filters have been proposed to enhance these medical images to overcome the problems while doing segmentation [1].

In particular, a local phase based filter[4]seems to be superior to intensity based filters [2]-[3] as it is immune to intensity and is worth to enhance the vessels at different widths. Morphological filters with multiscale Gaussian filters have also shown some interesting results [5]. But the disadvantage with these filters is that they do not consider the known vessel cross-sectional shape information. To overcome these disadvantages, the proposed model uses Cauchy filter [6] to enhance these medical images. And also the accuracy of the image is increased.

The remainder of this paper is structured as follows. Section 2 deals with related work done over the years. Section 3 deals with the proposed model with Cauchy filter as enhancement filter. Section 4 provides information about Data Sets and Evaluation Criteria. Section 5 provides the results of the model. Section 6 concludes the paper with future scope.

## 2.RELATED WORK

Filters are used to enhance structure of vessel in medical problems. Here, we review the three most influential filters.

### 2.1 Eigen value-based Filter [2]

Based on Hessian matrix eigen values this filter is used. For each pixel of a image with intensity f(x), the Hessian matrix can be formed by its 3 second derivatives. The filter is given as

$$F(x) = \begin{cases} 0 & \text{if } \lambda_1 > 0 \\ exp\left(-\frac{R_\beta^2}{2\beta^2}\right)\left(1 - exp\left(-\frac{S}{2c^2}\right)\right) & \text{otherwise} \end{cases} \quad (1)$$

### 2.2 Wavelet Filter [3]

The isotropic undecimated wavelet transform (IUWT) has been used for vessel segmentation. Applied to a signal c0 = f, subsequent scaling coefficients are calculated by convolution with a filter

$$c_{j+1} = c_j * h^{\uparrow j} \quad (2)$$

where $h_o$ is derived from the cubic B-spline. If f is multidimensional, the filtering can be applied separable in all dimensions. Wavelets are difference between two adjacent sets of scaling coefficients, i.e.,

$$w_{j+1} = c_j - c_{j+1} \quad (3)$$

the final set of scaling coefficients

$$f = c_n + \sum_{j=1}^{n} w_j \quad (4)$$

### 2.3 Local Phase-based Filter[4]

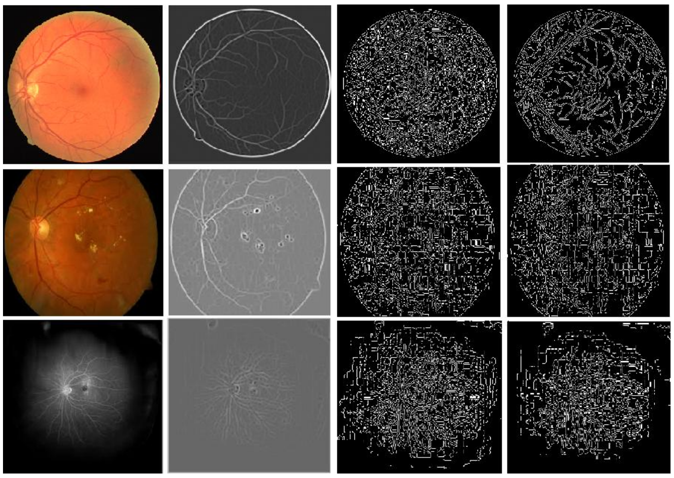
Structural information (e.g. lines and edges) of an image can be measured by this filter. For imaging applications, local phase uses quadrature filters under the concept of monogenic signals. The response at scale n

$$q_n^j(x) q_n = \sum_{j=1}^{J} q_n^j \quad (5)$$

is thus defined as in eq(5). The responses from each of the scales, is given below

$$P = \frac{\sum_{n=1}^{N} q_n \mid q_n \mid^{\beta}}{\sum_{n=1}^{N} \mid q_n \mid^{\beta}} \quad (6)$$

where number of scales is given an N and is β weighting parameter with value ≥ 1.



(A) (B) (C) (D)

**Fig -1**: Enhancement results produced by the eigenvalue-based method , wavelet-based method and local phase method , respectively on three dataset randomly choosen image. From top to bottom: DRIVE, STARE, and VAMPIRE. (B) Eigenvalue-based enhancement results. (C) Wavelet-based enhancement results.(D) Local phase based enhancement results.

**2.4 Infinite Perimeter Active Contour With Hybrid Region Information (IPACHI) Model[1]**

The IPACHI model was proposed for the segmentation of objects with irregular boundaries and so as to integrate hybrid region into the segmentation model. The energy of the IPACHI model is:

$$F^{IPACHI}(\Gamma, r_n) = \mathcal{L}^2(\gamma - \Gamma) + \sum_{n=1}^{N} \lambda_n R_n \quad (7)$$

$$\mathcal{L}^2(\gamma - \Gamma) \approx \int e^{-\left(\frac{\emptyset(x)}{\gamma}\right)^2} \quad (8)$$

where N is the total number of different region terms $\mathcal{L}^2$ is the 2D Lebesgue measure, Rn is the nth region information. Here we consider eq(8)for a large and even number α. Different region terms can be used alone (N = 1) or combined (N > 1) for specific applications.

## 3.CAUCHY FUNCTION AS FILTER KERNAL

Inspired by different enhancement models [2],[3], we propose a novel extension Cauchy PDF as the new kernel of the filter and show the accuracy of the vessel detection. We discovered that the Cauchy PDF shows the vessels patterns better and it is more flexible than existing methods, thus more vessels can be detected that uses Cauchy function[6].

The Cauchy PDF is defined as:

$$C(x) = \frac{1}{\pi\gamma\left[1 + \left(\frac{(x - x_0)}{\gamma}\right)^2\right]} \quad (9)$$

**TABLE- 1:** Performance of the three different enhancement methods(LP,WL,FR) on the DRIVE, STARE, VAMPIRE datasets. LP: local phased based filter; WL: wavelet based (IUWT) filter; FR: Frangi's eigenvalue based filter; Se: sensitivity; Sp: specificity; Acc: accuracy; AUC: area under curve

| Dataset | Enhance. | Acc | Se | Sp | AUC |
|---|---|---|---|---|---|
| | FR | 0.9967 | 0.3000 | 0.9967 | 0.6484 |
| DRIVE | WL | 0.9964 | 0.9899 | 0.9965 | 0.9935 |
| | LP | 0.9968 | 0.9924 | 0.9968 | 0.9970 |
| | FR | 0.9967 | 0.1250 | 0.9967 | 0.5609 |
| STARE | WL | 0.9964 | 0.9924 | 0.9965 | 0.9945 |
| | LP | 0.9968 | 0.9973 | 0.9968 | 0.9973 |
| | FR | 0.9967 | 0.1250 | 0.9967 | 0.5609 |
| VAMPIRE | WL | 0.9964 | 0.9865 | 0.9965 | 0.9915 |
| | LP | 0.9968 | 0.9944 | 0.9968 | 0.9956 |

where in eq(9) $x_o$ is the location parameter and γ is the scale parameter, these have an effect on the vessels detection. The propose one use local entropy thresholding algorithm that was introduced in[10] to produce the binary image of the Cauchy filtered image. By constructing the filter set using Cauchy kernel, the maximum response based on the direction of filter is calculated and the retinal image is convolved. This is more accurate than other competitive methods because entropy based thresholding algorithm is used. Furthermore, combining it with global thresholding, it is assured that vessels are correctly distinguished from non-vessels.

## 4. DATASETS AND EVALUATION CRITERIA

We have work with three retinal image datasets to evaluate our segmentation model. In this section, introduction to these datasets are provided and followed by evaluation metrics which is used in our experiments.

### 4.1 Datasets

#### 4.1.1Digital Retinal ImagesforVesselExtraction(DRIVE)

40 color images are used in this dataset, obtained in Netherlands in the course of a diabetic retinopathy screening program. At 45 degree field of view the image was acquired. Resolution of an retinal image is 768×584pixels.The 40 color images is divided into training set and test set, each consists of 20 images.

#### 4.1.2STructured of the Retina(STARE)

20 color retinal images are used which were captured by a TopCon TRV-50 fundus camera(Topcon, Tokyo, Japan) and the photos were digitized to 605×700 pixels. Out of 20, 10 of which show evidence of pathology.

#### 4.1.3Vessel Assessment and Measurement Platform for Images of the Retina(VAMPIRE)

8 ultra-wide retinal images are used. This dataset comprises eight ultra-wide field of view retinal angiographic images acquired with an OPTOS P200C camera(Optos PLC, Dunfermline, UK). Four are from a healthy retina while other four of the images are from an AMD retina. Each image has a size of 3900×3072 pixel.

### 4.2 Performance Parameters

The evaluation metrics are employed to evaluate the performance of the methods in terms of pixels including ,with this we also employed different performance parameters which is used to measure the quality of reconstruction image: ), specificity (Sp) = tn/(tn +fp), accuracy (Acc) = (tp + tn)/(tp + fp + tn + fn) and the areaunderareceiveroperatingcharacteristiccurve,AUC=(Se +Sp)/2,sensitivity(Se)=tp/(tp+fn),precision=tp/(tp+fp),recall=tp/(tp+fn),Fmeasure=2((precision*recall)/(precision+ recall)), tp, tn, fp and fn indicate the true positive (vessel pixels are correctly detected), true negative (vesselness pixels are correctly detected), false positive (vessel pixels are incorrectly detected), and false negative (vesselness pixels are incorrectly detected), respectively which is used for the proposed model.

## 5.EXPERIMENTS AND RESULTS

In this section we evaluate the performance of our proposed model and evaluate the effect of vessel enhancement on the performance across all three datasets. The experiments were performed in Matlab version 2015a on a PC 4GB RAM. The effect of three different vessel enhancement filters was evaluated which is shown in figure1.

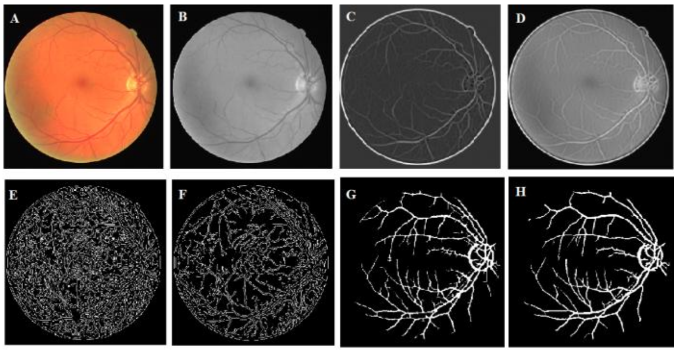



**Fig -2:** Illustrative results.(A) A randomly chosen image from DRIVE dataset. (B) Gray sale image of (A). (C)-(F) Enhancement results on (A) by using eigenvalue-based (FR), Cauchy-based, wavelet-based (IUWT),and local phase-based (LP) filters respectively. (G)-(H) IPACHI and Cauchy filter based segmentation respectively.

The performance parameters of the three datasets which are used commonly has been evaluated and shown in TableI. The results of proposed model are compared with IPACHI model on the DRIVE, STARE, and VAMPIRE datasets are demonstrated in TABLE II. It can be observed from TABLE II that the results of proposed model in terms of Se, Sp, Acc, AUC, precision, recall, f-measure, g-mean, MSE, PSNR outperform the competitor in the DRIVE, STARE and VAMPIRE datasets. The proposed model is efficient and effective for blood vessel segmentation. To emphasis the effectiveness of our model, we compare our model with other existing methods on two most popular public datasets: DRIVE and STARE. The VAMPIRE dataset is relatively new and few results in the literature. TABLE III. is the performance of our method and the others methods on both the DRIVE and STARE datasets in terms of sensitivity, specifity, accuracy and area under curve. The results have been ordered by the category of the previous methods such as supervised and unsupervised, in which the proposed method has better performance than before methods .

**TABLE- 2:** Performance of IPACHI and Cauchy segmentation models on the DRIVE, STARE, VAMPIRE datasets. MSE: mean square error; PSNR: peak signal to noise ratio.

| Performance Evaluation | DRIVE | STARE | VAMPIRE |
|---|---|---|---|

| | IPACHI | Cauchy | IPACHI | Cauchy | IPACHI | Cauchy |
|---|---|---|---|---|---|---|
| Accuracy | 0.9975 | 0.9982 | 0.9975 | 0.9982 | 0.9975 | 0.9982 |
| Sensitivity | 0.9765 | 0.9799 | 0.9686 | 0.9596 | 0.9123 | 0.9730 |
| Specificity | 0.9975 | 0.9982 | 0.9975 | 0.9982 | 0.9975 | 0.9982 |
| Area Under Curve | 0.9870 | 0.9890 | 0.9830 | 0.9789 | 0.9856 | 0.9549 |
| MSE (dB) | 0.19 | 0.19 | 0.11 | 0.10 | 0.07 | 0.06 |
| PSNR(dB) | 55.37 | 55.38 | 57.73 | 58.28 | 59.66 | 60.43 |
| Precision | 0.2427 | 0.2924 | 0.1918 | 0.1675 | 0.0742 | 0.2338 |
| Recall | 0.9765 | 0.9799 | 0.9596 | 0.9686 | 0.9123 | 0.9730 |
| F-measure | 0.3888 | 0.4503 | 0.3202 | 0.2853 | 0.3202 | 0.2853 |
| G-mean | 0.9870 | 0.9890 | 0.9829 | 0.9787 | 0.9540 | 0.9855 |

**TABLE-3:** Performance of different segmentation methods on DRIVE and STARE datasets. Se: sensitivity; Sp: specificity; Acc: accuracy; AUC: area under curve.

| METHODS | DRIVE | | | | STARE | | | |
|---|---|---|---|---|---|---|---|---|
| | Se | Sp | Acc | AUC | Se | Sp | Acc | AUC |
| Marin et.al[7] | 0.706 | 0.980 | 0.945 | 0.843 | 0.694 | 0.981 | 0.952 | 0.838 |
| You et.al[8] | 0.741 | 0.975 | 0.943 | 0.858 | 0.726 | 0.975 | 0.949 | 0.851 |
| Bankhead et.al[3] | 0.703 | 0.971 | 0.9371 | 0.837 | 0.758 | 0.950 | 0.932 | 0.854 |
| Al-Diri et.al[9] | 0.728 | 0.955 | - | 0.842 | 0.752 | 0.968 | - | 0.860 |
| IPACHI[1] | 0.976 | 0.9975 | 0.9975 | 0.9870 | 0.9686 | 0.9975 | 0.9975 | 0.978 |
| **Proposed method** | 0.9799 | 0.9982 | 0.9982 | 0.9890 | 0.9596 | 0.9982 | 0.9982 | 0.9830 |

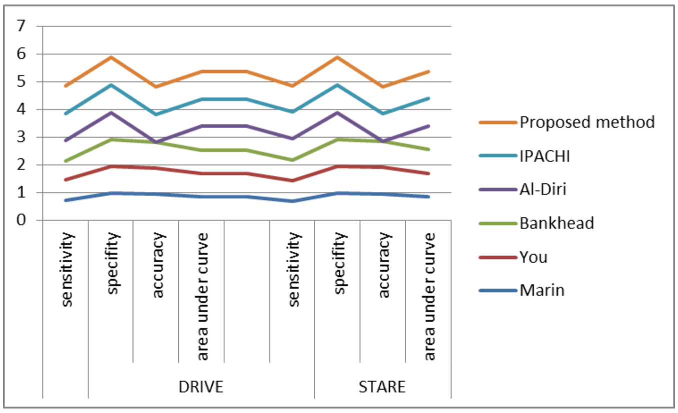



**Chart -1**: Performance of different segmentation method with respect to TABLE-3

## 6. CONCLUSION

We propose a new kernel function in vessel segmentation problem for the retinal blood vessels filter based segmentation of active contour model. This model has been applied to three publicly available retinal datasets images and shows the good accuracy. The detection of blood vessels is essential and an important step for vessel analysis to perform more advanced analysis, such as diameter measurement and twisted vessels, calculation of the arteriovenous ratio, and diagnostic and prognostic values of eye disease and systematic diseases like stroke, hypertension etc. In conclusion, all in all, from the results, it is deduced that the offered filter with Cauchy PDF as its kernel to detect blood vessels in the digital retinal images is a better choice. This is a powerful tool for analyzing vasculature for better management of a wide spectrum of vascular-related diseases.

This can be extended by extracting Statistical Texture Parameters [11] which are useful in real time pattern recognition application like Military and Medical Application. This model is also suited for segmentation problems in images of other organs acquired by different imaging techniques such as CT, MRI, and X-ray images.

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