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Retinal Vessel Extraction with Segmentation

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Abstract:- **vessel extraction for retinal image play crucial role in medical images for proper diagnosis and treatment of various diseases like diabetic retinopathy, hypertensive retinopathy and various cardio vascular diseases. In this paper we propose a novel technique for automatic analysis of fundus retinal image using improved vessel of infinite perimeter active contour model. This approach uses of intensity information and local phase based enhancement filter technique and Cauchy based matched filter provide better accuracy. The performance evolution is carried on DRIVE data set and real images too. The results show good performance and previous IPACHI method.**

Index terms-vessel, segmentation, local phase, infinite perimeter, active contour, fundus

I. INTRODUCTION

Automated vessel extraction using segmentation techniques helps to proper diagnosis and early detector of disease. Recently, rapid development in methods for vessel segmentation, still it's a challenging problem due to poor image quality. Many researchers provide that supervised and unsupervised methods for vessel segmentation filter based methods are showing good performance. Improved image processing modalities may provide proper diagrammatic whole; through the image taken by fundus cameras have poor contrast towords background retina.

The approach available for blood vessel segmentation can be classified based on edges, morphology methods and filter techniques. Blood vessels are linear structures, so edge based method [4] have different edge detector operators like sobel, Prewitt, canny and Roberts works on sharp edges only. As the vessel length in small retinal images, so the edge based techniques does not provide accurate blood vessel retina.

Mathematical morphology methods have prior knowledge on shape feature and they are filtered from the background for segmentation. Zana and Klein cross curvature evolution to separate the vessel from retinal image with combined morphological filters such as path opening in combined filters with multi scale Gaussian filters shown better result [4]. The main disadvantage of morphological method is they do not consider the known vessel cross-sectional shape information and the use of overly long stuctures may cause difficulty in detecting highly tortuous vessels [1].

In contrast, active contour models have good performance in many challenging segmentation problems including vessel segmentation. Here we focused on the new active contour model to improve the accuracy of blood vessels. Active contour models are used for the object tracking, shape recognition, segmentation, edge detection and stereo matching. We have many active contour models including ribbon of twins(ROT) model is difficult to formulate and optimize [1], CV and DRLSE models are easy to formulate and optimize but the shortest smooth boundary length makes then not suitable for vessel segmentation problem. The infinite perimeter active contour model shows good performance but this method misses some useful information at the capillaries. On the other hand, a new method retinal vessel extraction with segmentation has shown convincing performance in detection of small oscillatory stuctures. This model shows the good performance than the all existing methods with three public retinal image datasets and with real diseased images also. The datasets are available for the research and application purpose.

II.RELATED WORK

A. Active Contour Models:

1) Chan-VESE Algorithm:

The Chan vese algorithm is especially useful in case where an edge-base segmentation algorithm will not suffice, since it relies on global properties grey level intensities, contour lengths, and region areas. Rather than local properties such as gradients. It can deal gracefully with noisy images, blurry images and images where the foreground region has complicated topology[5]; multiple holes, disconnected regions etc.

Although, the Chan-vese algorithm is prohibitively slow for some applications. Depending on the type and size of the image and the number of iterations need. Without loss of generality, here we choose the 2-dimensional(2D) segmentation problem as an example. Denoting a given image by $u_0(\mathbf{x})$, $\mathbf{x} = (x_1, x_2)$, the CV model can be

formulated as the CV model can be formulated as the energy minimization problem below.

E^{CV}= (Γ,a_1,a_2) = $\mu_{cv}H^1$ (Γ) + $\lambda_{1cv}\int_{inside\ (\Gamma)}$ |v_0(X) - $a_1|^2$dx + λ_{2cv} $\int_{outside\ (\Gamma)}$ |v_0(X) - $a_2|^2$dx (1)

Where a_1 and a_2 are the averages of v_0(X) inside and outside(Γ) respectively, μ_{cv},λ_{1cv} and λ_{2cv} are non-negative fixed parameters.

E^{CV}= (Ø(x),a_1,a_2) = $\mu_{cv}\int_{\Omega}|\nabla H(Ø(X))dx$ + $\lambda_{1cv}\int_{\Omega}$ |v_0(X) - $a_1|^2H(Ø(X))$dx +$\lambda_{2cv}\int_{\Omega}$ |v_0(X) - $a_2|^2(1-H(Ø(X)))$dx (2)

2) Distance Regularized Level Set Evolution (DRLSE):

$E^{DRLSE}((Ø(X))$=μR$(Ø(X))$ + $\lambda L_g(Ø(X))$ + $\alpha Ag(\varphi(\mathbf{x}))$ (3)

WhereR$(Ø(X))$is the distance regularization term, $L_g(Ø(X))$ is the external energy term which indicated the length functional, and $Ag(\varphi(\mathbf{x}))$ is the area penalization term.

3) Ribbon of twins(ROT) model:

We introduced a new parametric active contour model suitable for segmentation of retinal vessels and other fine,noisy, linear structures. Two twins of contours represent a ribbon along vessel, with one twin on each edge of the vessel. Each contour consist of two contours, one side and one outside the vessel. Each contour consist of number of nodes. Corrsponding node on four contours connected together to form a single integrated model. The two outside contours are connected by pull forces to the inside contours, while the inside contours aren connected by push forces to each other[7].

$E^{ROT}(c(s))$= $\int_0^1 E_c^{int}$ (**v**(*s*)) +E_c^{pho} (**v** (*s*)) +E_c^{rot} (**v** (*s*)) (4)

E_c^{int} *and* E_c^{pho} Denotes the internal, photometric, and ROT model energy functions, respectively. **v***c*(*s*) are four linked active contours.

4) Geodesic active contour model:

It provides an alternative model for edge detection that is derived from the classical active contour model. This type of approach is equivalent to finding geodesic distance of two points on carefully chosen Riemannian space. The intrinsic nature of the model, changes in geometry of counters are handle automatically, hence multiple objects could be recognized simultaneously. So the need for preprocessing the image is reduced. Also, allowing object with non- ideal to recognize. The advantage of this model is its ability in capturing holes in objects. And one of the disadvantages of this model is that it is unable to work with texture image.

(∂Ø(x))/∂t = − Re(LP)|∇φ(x)| + ακ|∇φ(x)| (5)

4) IPACHI model:

The existing a novel extension so as to integrated hybrid region information in to the segmentation model. This method segment the object with irregular boundaries [1].

F^{IPAC}(Γ, $a1$, $a2$) = $L^2(\gamma-\Gamma)$ + $\lambda_1\int_{inside\ (\Gamma)}$|$v_0$(X) - $a_1|^2$dx + $\lambda_2\int_{outside\ (\Gamma)}$ |v_0(X) - $a_2|^2$dx (6)

Where L^2 is the 2D Lévesque measure of the γ- edge of the neighbourhood of the set Γ and λ_1 *and* λ_2 are fitting term parameters.

Level set methods have been widely used in

$F^{IPAC}((Ø(X))$=$\int_{\Omega}$f($\frac{|Ø(X)|}{\gamma}$) + R(Ø(X)) + $\lambda 1\int_{\Omega}$|v_0(X) - $a_1|^2$dx $H(Ø(X))$dx+ $\lambda_2\int_{\Omega}$ |v_0(X) - $a_2|^2(1-H(Ø(X)))$dx (7)

B. Typical vessel filters:

Filters are useful to enhance the vessel-like stuctures and play a very crucial role in the vessel segmentation.

1) Eigen value-based filter:

The multi scale second local structure of an image(Hessian) is examined with the purpose of depending a vessel enhancement filter. A vessel measure is obtained on the basis of all Eigen value of Hessian. It supresses the back ground noise and vessel enhancement in maximum intensity projection and volumetric display [13].

$$V_0(S)=\begin{cases} 0 & if\ \lambda_2>0\ or\ \lambda_3>0, \\ \left(1-\exp\left(-\frac{RA^2}{2\alpha^2}\right)\exp\left(-\frac{RB^2}{2\beta^2}\right)\right)\left(1-\exp\left(-\frac{S^2}{2C^2}\right)\right) & \text{otherwise} \end{cases} \quad (8)$$

Where *α*, *β* and *c* are thresholds which control the sensitivity of the line filter to the line filter to the measures R_A, R_B and S.

2) Cauchy based matched filter:

The matched filter uses a kernel function to approximate the vessel's cross section. The Cauchy PDF imitates the vessels patterns better behaves more flexible than the Gaussian matched filter, thus more vessels can be

detected via a matched filter uses Cauchy function as the template generator [2]. The Cauchy PDF is defined as

$$C(x)=\frac{1}{\Pi r[1+\left(\left(\frac{x-x_0}{r}\right)\right)^2]} \qquad (9)$$

The Cauchy based matched filter gives more flexible to detect blood vessels in retinal images.

3) Isotropic Un decimated wavelet filter:

The isotropic decimated wavelet transform (IUWT) is useful for the vessel segmentation. It gives the good result, but it gives both vessels and the nerves in the resultant image.

$$f=k_n + \sum_{i=1}^{n} x_i \qquad (10)$$

4) Local phase –based filter:

Local –phased-based filter gives the structural information i.e. lines and edges of an image. It enhances vessels in a more precise way and produced promising segmentation results. It gives only blood vessels in the resultant image. The result is good but still we need the clarity image.

III. CAUCHY BASED MATCHED FILTER WITH IPACHI

In this paper, a novel matched filter based on a new kernel function with Cauchy distribution along with IPACHI introduced to improve the accuracy of the segmentation. The Cauchy based matched filter useful to improve the vessel detection capacity.

The matched filter detects features in an image which are mostly likely to a predefined known as kernel. In the matched filter vessels are assumed to be piece-wise line with the cross sectional intensity changes similar to predefined kernels. To detect lines in every direction, a set of kernel is required.

Previous authors, for vessel detection they tried with Gaussian matched filters. Gaussian matched filter uses the Gaussian function to detect vessels of the retina. Cauchy PDF imitates the vessels the vessels pattern better behaves more flexible than Gaussian matched filter, thus more vessels can be detected via matched filter uses Cauchy function as the template generator [2]. The Cauchy PDF is defined as

$$C(x)=\frac{1}{\Pi r[1+\left(\left(\frac{x-x_0}{r}\right)\right)^2]}$$

The retinal blood vessels do not vanish as fast as the Gaussian function. Therefore, the Cauchy characteristics first the vessels lines better than its Gaussian counterpart and thus it is makes it much more flexible to detect blood vessels in retinal images. By improving detection capacity of the vessels through Cauchy based matched filter and adding thus feature to the IPACHI model we are getting the accurate segmentation than the normal IPACHI segmentation.

The IPACHI model integrates hybrid region information into segmentation model. The energy of the IPACHI is

$$F^{\text{IPAC}}(\Gamma, a_1, a_2) = L^2(\gamma - \Gamma) + \lambda_1 \int_{inside\,(\Gamma)} |v_0(X) - a_1|^2 dx + \lambda_2 \int_{outside\,(\Gamma)} |v_0(X) - a_2|^2 dx$$

In this IPACHI model we are using the different filters. And for thus filters at the early stage we are adding Cauchy based matched filter to the IPACHI for accurate segmentation results.

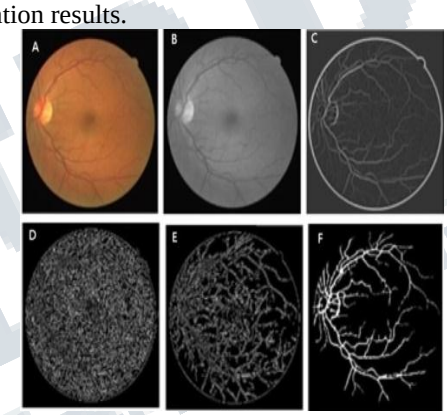

Fig:1:IPACHI segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result (D) Wavelet enhanced result (E) Local enhanced result (F) IPACHI result.

III. EXPERIMENTS AND RESULTS

For this proposed model we are using the DRIVE data set. And all the experiments were performed in MATLAB version 2013a.

Here we tried Cauchy based IPACHI segmentation with different edge detectors at different resolutions i.e. 128, 256 and 512. We tried with prewitt, sobel, Robert and canny edge detector. Edge based methods find the vessel edges with an edge detector such as Sobel, Canny and Prewitt operators. These approaches work properly on distinct and sharp edges only. The results of different edge detectors with different resolutions are shown below.

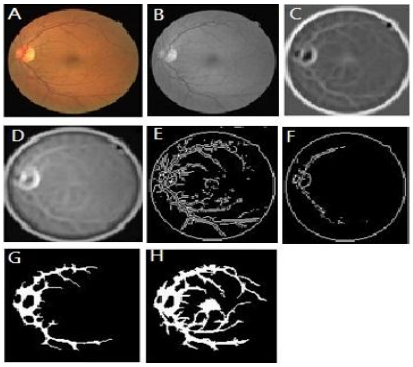

Fig:2:IPACHI with Cauchy segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result (D) Cauchy result (E) Wavelet enhanced result (F) Local enhanced result (G) IPACHI result (H) Cauchy segmentation. For the above results we used prewitt edge detector with 128 resolutions.

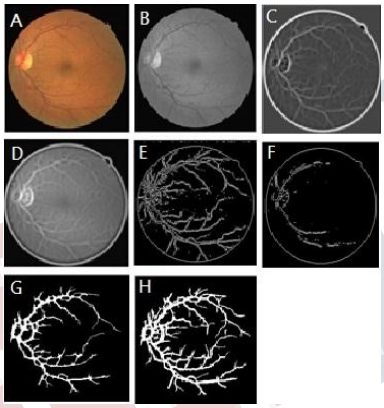

Fig:3:IPACHI with Cauchy segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result (D) Cauchy result (E) Wavelet enhanced result (F) Local enhanced result (G) IPACHI result (H) Cauchy segmentation.

For the above results we used prewitt edge detector with 256 resolutions.

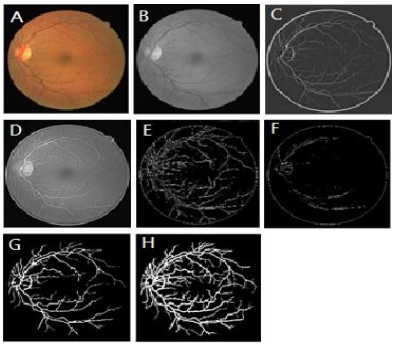

Fig:4:IPACHI with Cauchy segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result (D) Cauchy result (E) Wavelet enhanced result (F) Local enhanced result (G) IPACHI result (H) Cauchy segmentation.

For the above results we used prewitt edge detector with 512resolutions.

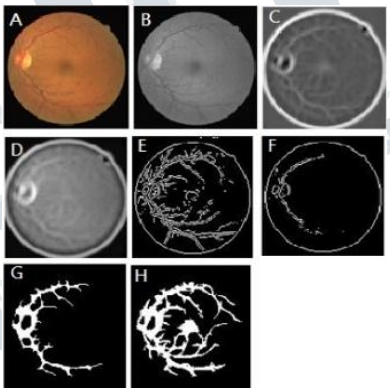

Fig:5:IPACHI with Cauchy segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result (D) Cauchy result (E) Wavelet enhanced result (F) Local enhanced result (G) IPACHI result (H) Cauchy segmentation.

For the above results we used sobel edge detector with 128 resolutions.

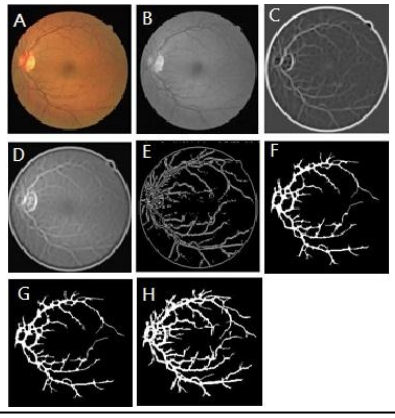

Fig:6:IPACHI with Cauchy segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result (D) Cauchy result (E) Wavelet enhanced result (F) Local enhanced result (G) IPACHI result (H) Cauchy segmentation.

For the above results we used sobel edge detector with 256 resolutions.

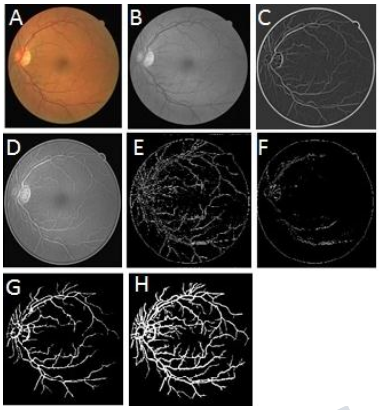

Fig:7: IPACHI with Cauchy segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result (D) Cauchy result (E) Wavelet enhanced result (F) Local enhanced result (G) IPACHI result (H) Cauchy segmentation.

For the above results we used sobel edge detector with 512 resolutions.

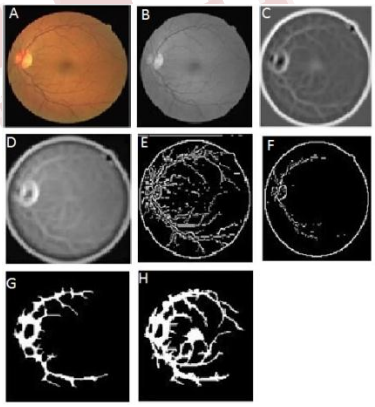

Fig:8:IPACHI with Cauchy segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result (D) Cauchy result (E) Wavelet enhanced result (F) Local enhanced result (G) IPACHI result (H) Cauchy segmentation.

For the above results we used Roberts's edge detector with 128 resolutions.

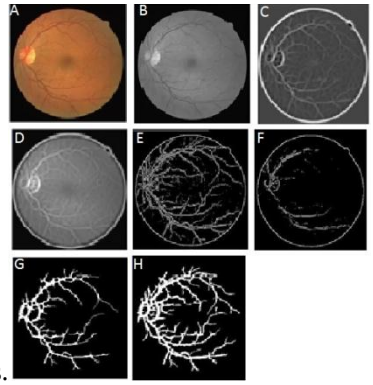

Fig:9:IPACHI with Cauchy segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result (D) Cauchy result (E) Wavelet enhanced result (F) Local enhanced result (G) IPACHI result (H) Cauchy segmentation.

For the above results we used Roberts's edge detector with 256 resolutions.

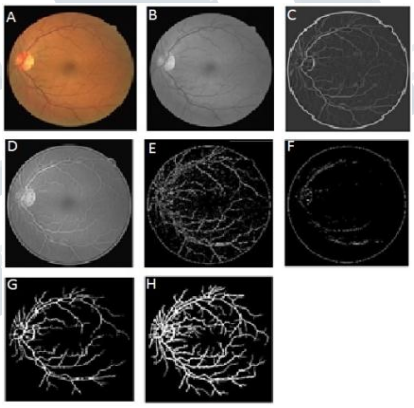

Fig:10:IPACHI with Cauchy segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result (D) Cauchy result (E) Wavelet enhanced result (F) Local enhanced result (G) IPACHI result (H) Cauchy segmentation.

For the above results we used Roberts's edge detector with 512 resolutions.

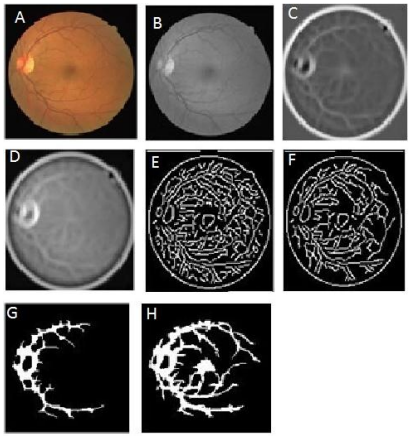

Fig:11:IPACHI with Cauchy segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result (D) Cauchy result (E) Wavelet enhanced result (F) Local enhanced result (G) IPACHI result (H) Cauchy segmentation.
For the above results we used canny edge detector with 128 resolutions.

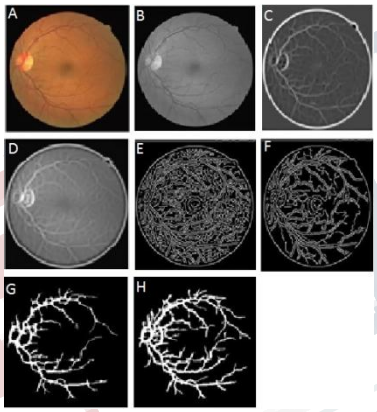

Fig:12:IPACHI with Cauchy segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result (D) Cauchy result (E) Wavelet enhanced result (F) Local enhanced result (G) IPACHI result (H) Cauchy segmentation. For the above results we used canny edge detector with 256 resolutions.

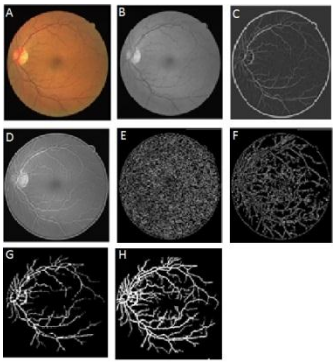

Fig:13:IPACHI with cauchy segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result (D) Cauchy result (E) Wavelet enhanced result (F) Local enhanced result (G) IPACHI result (H) Cauchy segmentation.For the above results we used canny edge detector with 512resolution.By observing all the above results canny edge detector with 512 resolution give the accurate result at each stage.

IV.APPLICATION TO REAL DISEASED IMAGES:

1) Diabetic Retinopathy:

Here we applied our algorithm to some real disease images. Here we taken input image is the diabetic retinopathy image. Diabetic retinopathy, the most common diabetic eye disease, occurs when blood vessels in the retina change.sometimes these vessels swell and leake fluid or even close off completely. In other case, abnormal new blood vessels grow on the surface of retina. The retina is a thin layer of light-sensitive tissue that the back of the eye. Light rays are focused onto the retina, where they are transmitted to the brain and interpreted as the images you see. The macula is a very small area at the center of the retina. It is the macula that is responsible for your pinpoint vision, allowing you to read, sew recognize a face. The surrounding part of the retina, called the peripheral retina. Diabetic retinopathy usually affects both eyes. People who have diabetic retinopathy often don't notice changes in their vision in the disease's early stages. But as it progresses, diabetic retinopathy usually causes vision loss that many cases canot be reversed.

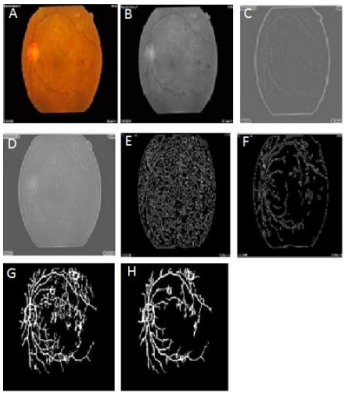

Fig:14:IPACHI with Cauchy segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result(D) Cauchy result (E) Wavelet enhanced result (F) Local enhanced result (G) IPACHI result (H) Cauchy segmentation.

2) HYPER TENSIVE RETINOPATHY:

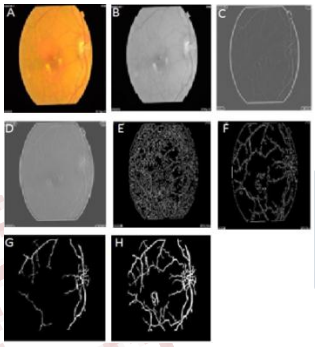

Fig:15:IPACHI with Cauchy segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result (D) Cauchy result (E) Wavelet enhanced result (F) Local enhanced result (G) IPACHI result (H) Cauchy segmentation.

The retina is the tissue layer located in the back of our eye. This layer transforms light into signals that are then sent to the brain for interpretation. When your blood pressure is too high, the retina's blood vessel walls may thicken. This may cause your blood vessels to become narrow, which then restricts blood from reaching the retina. In some cases, the the retina becomes swllen. Overtime, high blood pressure can cause damage to retina's blood vessels, limit the retina's function and put pressure on the optic nerve , causing vision problem. This condition called hypertensive retinopathy(HR).

***3) ALBONITIC FUNDUS*:**

Method	Se	Sp	Acc
IPACHI	0.743	0.984	0.861
IPACHI with Cauchy segmentation	0.749	0.987	0.865

Medical signs that can be detected from observation of eye fundus include hemorrhages, exudates, and cotton wool spots, blood vessel abnormalities and pigmentation. The eye's fundus is the only part of the human body where the microcirculation can be observed directly. This is the hereditary disease. And it is mostly occur in the persons have golden-colored and the skin is described as white.

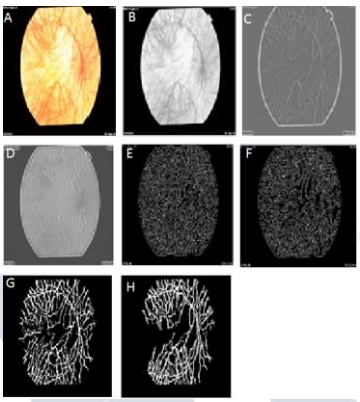

Fig:16:IPACHI with Cauchy segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result (D) Cauchy result (E) Wavelet enhanced result (F) Local enhanced result (G) IPACHI result (H) Cauchy segmentation.

4) FULL THICKNESS MOLICULAR HOLE (FTMH):

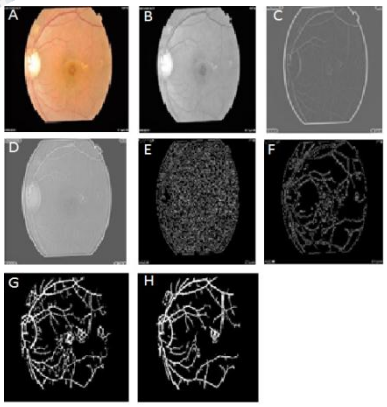

Fig:17:IPACHI with Cauchy segmentation results (A) DATASET (B) Enhancement result (C) Eigen enhanced result (D) Cauchy result (E) Wavelet enhanced result (F) Local enhanced result (G) IPACHI result (H) Cauchy segmentation.

A Full Thickness Macular Hole (FTMH) is a hole in the retina that occurs in the central part of the macula. FTMHs are relatively common- about 3 in every 1000 persons over the age of 55 develop a macular hole.

Table:1: performance of IPACHI and IPACHI with Cauchy segmentation on the DRIVE data set Se: sensitivity, Sp: specificity, Acc: accuracy.

V.CONCLUSION

In this paper, we have proposed Retinalvessel extraction with segmentation for vessel segmentation problem. For this model we are using DRIVE dataset as the input. Accurate vessel segmentation is the more complicated problem in now a day. The IPACHI segmentation gives good results but to get more accurate result we are adding Cauchy based matched filter to the IPACHI segmentation at the early stage. Due nature of Cauchy filter it will brighten the vessel and because of this nature the detection capacity is improved and more vessels can be accurately segmented. This will be powerful tool for analyzing vascular for better management of a wide spectrum of vascular- related disease.

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