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Performance Analysis For Blood Vessel Segmentation In Hypertensive Retinopathy

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***Abstract*-Hypertensive Retinopathy (HR) is one of the most common retinal diseases. Normally, the high blood pressure will affect the various organs of the biological system, one of them is eye. The retinal blood circulation is affected, due to the damages caused by the high blood pressure; this disease is termed as the Hypertensive Retinopathy. This disease is diagnosed from the retinal images, specifically from the blood vessels of the retina. Some of these measures for finding HR using digital image are Segmentation of blood vessels, measurement of tortuosity, diameter measurement, finding the artery vein ratio.A method is proposed for segmenting the blood vessels which is performed in various steps. The footprint of the blood vessels is more visible in the gray scale image and green extracted image. The noise in the image is removed using Gabor Wavelet and Sharpening Spatial filters. The segmentation is performed based on the approximation so the Rough Entropy is well suits to this retinal image to distinguish the blood vessels from the other parts. The Evaluation measure such as Probability Rand Index (PRI), Global Consistency Error (GCE), Local Consistency Error (LCE) measures are used for comparison process between gray scale image and green extracted image which gives better segmentation result.**

Keywords-Retinal image, Gabor wavelet, Rough entropy, Evaluation measure.

I. INTRODUCTION

Hypertensive Retinopathy is one of the leading retinal disease which damage retina and retinal circulation. Blood vessel segmentation is an important matter for assessing retinal abnormalities and diagnoses of many diseases. The segmentation of vessels is complicated by the huge fluctuations in local contrast, especially in case of the small vessels. In this paper, we suggest a segmentation method of texture based vessel segmentation to overcome this trouble[1].

The various signs of Hypertensive Retinopathy are as follows,Narrowing of blood vessels,Fluid oozing from the blood vessels,Spots on the retina known as cotton wool spots and hard exudates,Swelling of the macula and optic nerve,Bleeding in the back of the eye. The traditional classification of hypertensive retinopathy typically consists of four grades of hypertensive retinopathy with increasing severity.

Grade 1 consists of "mild" generalized retinal arteriolar narrowing; grade 2 consists of "more severe" generalized narrowing, focal areas of arteriolar narrowing, and AV nicking; grade 3 consists of grade 1 and 2 signs plus the presence of retinal hemorrhages, microaneurysms, hard exudates and cotton wool spots; and grade 4, sometimes referred to as accelerated (malignant) hypertensive retinopathy, consists of signs from the three previous grades with the addition of optic disc swelling and macular edema. One of the major limitations of this classification system is the difficulty in distinguishing early hypertensive retinopathy grades (e.g., grade 1 from grade 2)[2].

The DRIVE database has been established to enable comparative studies on segmentation of blood vessels in retinal images. The Image Science Institution Research community is invited to test algorithm on their database. Almost 40 sample retinal images are taken from this database and manually segmented image are also taken from the DRIVE database for analyzing the performance of the Rough entropy segmented image.

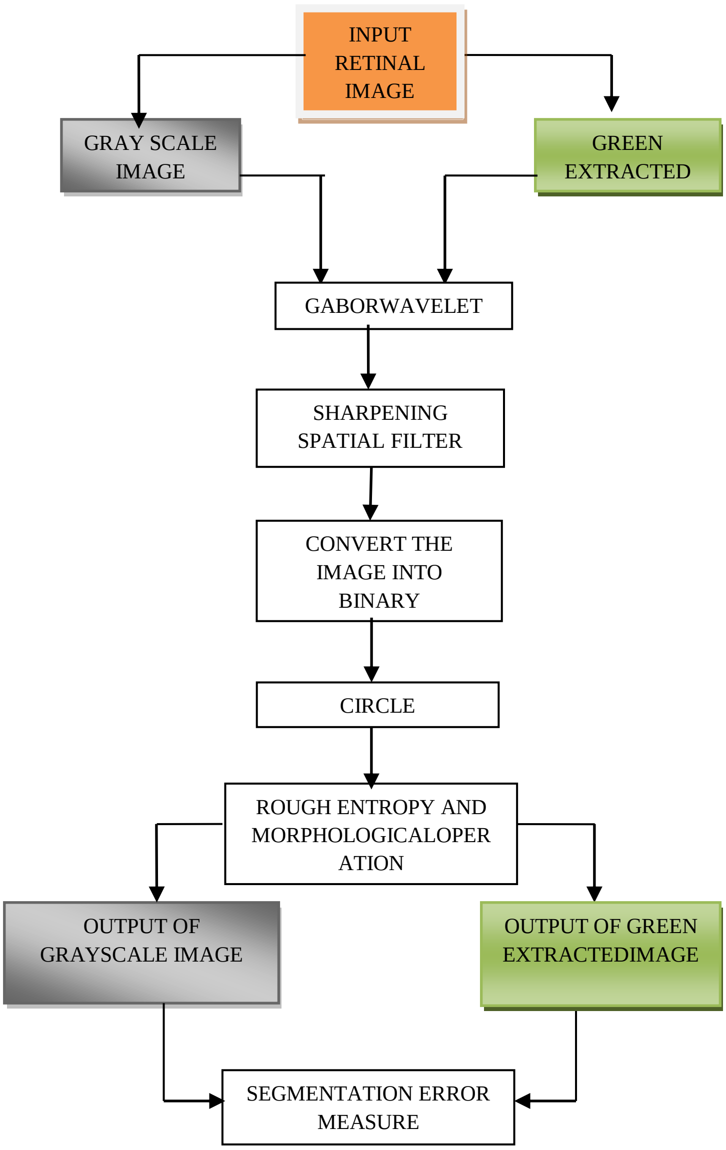


Figure 1. Flow Diagram of Blood Vessel Segmentation Process

II. RELATED WORK

M. UsmanAkram and Shoab A. Khan(2014), proposed the method uses 2-D gabor wavelet for vessel enhancement due to their ability to enhance directional structure and a new multilayered thresholding technique for accurate vessel segmentation. The strength of proposed segmentation technique is that it performs well for large variations in illumination and even for capturing the thinnest vessels.[4]

João V, B. Soares et al.,(2006), proposed the method produces segmentations by classifying each image pixel as vessel or non vessel, based on the pixel's feature vector. Feature vectors are composed of the pixel's intensity and two-dimensional Gabor wavelet transform responses taken at multiple scales. The Gabor wavelet is capable of tuning to specific frequencies, thus allowing noise filtering and vessel enhancement in a single step. We use a Bayesian classifier with class-conditional probability density functions (likelihoods) described as Gaussian mixtures, yielding a fast classification, while being able to model complex decision surfaces.[5]

M.M. Fraza and P. Remagnino(2006), proposed the technique to review, analyze and categorize the retinal vessel extraction algorithms, techniques and methodologies, giving a brief description, highlighting the key points and the performance measures.[3]

III. PROPOSED TECHNIQUE

The Preprocessing and Enhancement steps involved in the blood vessel segmentation are discussed in this chapter. The Retinal image is taken as input for the preprocessing. It is an RGB image.The gray scale image and green extracted image are obtained from the preprocessing and these images are further used as input for enhancement process.The Gabor wavelet and Sharpening spatial filter are applied for the image enhancement.

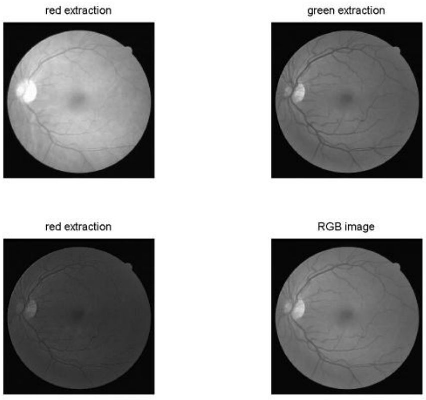


Figure 2. Extraction of RGB band

Original Retinal image is in RGB color model having an almost empty blue band where as red is normally saturated but green channel gives good representation of retinal image featureis shown in the above Figure 2.

A. Preprocessing

The preprocessing is required in order to distinguish the blood vessels from the other parts in the retinal image. The retinal image is the input of this phase. It is an RGB image. The grayscale image and green extracted image are obtained from the preprocessing phase. The grayscale image is obtained by converting the RGB retinal image into grayscale. The green extracted image is obtained by extracting of green intensity values from the given RGB retinal image. The blood vessels are highly visible in green intensity when compared with the red and blue intensities of the retinal image.The preprocessing of a sample image is shown in the Figure.3.

(a) (b) (c)

Figure 3. a)original image b)gray scale image c)green extracted image

B. Enhancement

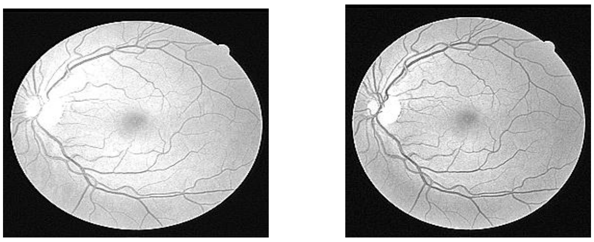
The further enhancement is performed to increase the intensity of the blood vessels in the retinal image. The grayscale image and green extracted image are taken as the input for this phase. Gabor Wavelet and Sharpening spatial filters are applied to enhance the preprocessed image.

1) Gabor Wavelet

Gabor wavelets are used here to detect edges, corners and blobs. Gabor functions are frequently used for feature extraction, especially in texture-based image analysis (e.g., classification, segmentation or edge detection) and more practically in face recognition. Many of image processing tasks can be seen in terms of a wavelet transform. Informally speaking, the image can be seen under the lens with a magnification given by the scale of a wavelet. In doing so,we can only see just the information that is determined by the shape of the used wavelet. The Gaboratoms can also be seen in the words of a wavelet transform .Specifically, Gabor wavelets are createdfrom one particular atom by dilation (and rotation in the two-dimensional case). These Gabor waveletsprovide a complete image representation.[6,7]

The Gabor Wavelet transform could extract both the time (spatial) and frequency info from a given signal.The tunable kernel size allows it to execute multi-resolution analysis. The tunable kernel size results in different time - frequency resolution pair and the size is related to the analytical frequency. For instance, smaller kernel size (in the time domain) has higher resolution in the time domain but lower resolution in the frequency domain, and is utilized for higher frequency analysis.Bigger kernel size has higher resolution in the frequency domain, butt lower resolution in time domain, and is utilized for lower frequency analysis. Due to directional selectiveness capability the Gabor wavelet is used for blood vessel segmentation to enhance the vascular pattern is shown in the Figure 4.[6, 7]

Gabor wavelets are used complex functions constructed to serve as a basis forFourier transforms in information theory applications. They are much related to Morlet wavelets. They are also personally related to Gabor filters.The important property of the riffle is that it minimizes the product of its standard deviations in the time and frequency domain. Still, they suffer the downside of being non-orthogonal, so efficient decomposition into the ground is difficult. Since their inception, various applications have appeared, from image processing to analyzing neurons in the human visual system[6, 7].

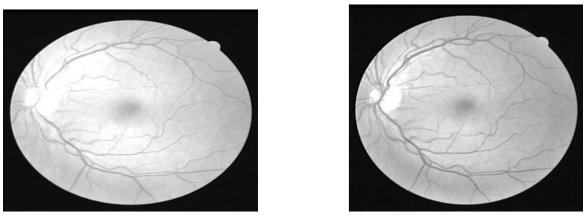


(a) (b)

Figure 4. Gabor Wavelet applied to a)gray scale image b)green extracted image

2) Sharpening Spatial Filter

Spatial filtering term is the filtering operations that are performed directly on the pixels of an image. The simple objective of sharpening is to highlight fine detail in an icon or to enhance detail that has been obscured, either in error or as a life like consequence of a particular method of image acquisition. Sharpening could be achieved by spatial differentiation.



(a) (b)

Figure 5. Sharpening spatial filter to a)gray scale image b)green extracted image

The main objective of sharpening spatial filter is to highlight the transformation in intensity. We used a sharpening filter to enhance and increase the intensity so that the vascular pattern will appear a darker. The sharpening can be done with the result of Gabor wavelet. After applying sharpening the image can be converted into binary then circle can be removed for further segmentation.The sharpening filter applied to gray scale and green extracted image are shown in the above Figure 5.

C. Segmentation

The segmentation plays an important role in blood vessel segmentation for diagnosing the disease in Retinopathy. The enhanced image is used for further segmentation process. The rough entropy is applied to the enhanced image. Then the various morphological operations are performed on the image to extract the blood vessels. The segmented image is compared to the manually segmented image based on their performance measures for both the grayscale image and green extracted image.

1) Rough Entropy

As an efficient quantity of uncertainty, the entropy, proposed by Shannon, has been a useful mechanism for characterizing the data content in several modalities and applications in many various areas. In order to measure the uncertainty in rough sets, many researchers have applied the entropy to rough sets, and proposed different entropy models in rough sets. Rough entropy is an extend entropy to measure the uncertainty in rough sets.

Given an information system $IS = (U, A, V, f)$, where U is a non-empty finite set of objects, $A$is a non-empty finite set of attributes. For any $B \subseteq A$, let $IND(B)$ be the equivalence relation as the form of $U/IND(B) = \{B_1, B_2, ..., B_m\}$. The rough entropy $E(B)$ of equivalence relation $IND(B)$ is defined in the equation 1.

$$E(B) = -\sum_{i=1}^{m} \frac{|B_i|}{|U|} \log \frac{1}{|B_i|} \quad (1)$$

Where $\frac{|B_i|}{|U|}$Denotes the probability of any element, $x \in U$ being in equivalence class B_i; $1 <= i <= m$. And $|M|$ denotes the cardinality of set *M*.In the above definition, for any $B \subseteq A$, if $U/IND(B) = \{U\}$, then the rough entropy $E(B)$ of equivalence relation $IND(B)$ achieves the maximum value $log|U|$. And if $U/IND(B) = \{\{x\} : x \in U\}$, then the rough entropy $E(B)$ of equivalence relation $IND(B)$ achieves the minimum value 0.[10]

2) Rough Entropy Based Blood Vessel Segmentation

Rough Entropy is applied for segmentation of blood vessel segmentation. Since the Original image is converted into Binary image there are only two pixel values 1-White 0-Black. When it is converted to binary image the vessel part becomes white so the region of interest is white (1) pixel. First column wise rough entropy is applied, for each column, row that have white pixels are counted and it is taken as probability. For ex: In first Column rows 7,10,56,120 has a white pixel, then count will be 4 and probability is 4/256 since thereare 256 rows so total probability is 256 out of which 4 has occurred.

Similarly for each column total row that has white pixel are divided by total rows to calculate probability for each column. So the Region of Interest is high intensity (white pixel) where tumor part is present. When probability is calculated for each column rough entropy is applied. When rough entropy is calculated, the threshold is set based on which the white pixels with least count are removed. Similarly the procedure is repeated for each row number of white pixels in column is divided by length of column to calculate probability row wise. When probability is calculated for each row rough entropy is applied. Finally the row and column that has higher intensity pixel taken as output which is blood vessel segmentation.

Rough entropy measures calculation of the cluster centers which is based on lower and upper approximation generated by assignment of data objects to the cluster centers. Roughness of the cluster center is calculated from lower and upper approximations of each cluster center. In the next step, rough entropy is calculated as the sum of all entropies of cluster center roughness values. Higher roughness measure value describes the cluster model with more uncertainty at the border is shown in the equation 2.

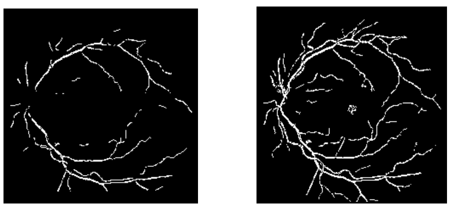
$$H(x) = -\sum_{j=1}^{m} p(a_j) \sum_{i=1}^{n} \left(\frac{c_i}{a_i}\right) logp\left(\frac{c_i}{a_j}\right) \quad (2)$$

Where H(x) is the rough entropy image, p is the probability for an image, $a_1 \ldots a_n$ are the attributes and $c_1 \ldots c_n$ are decision values.

3) Morphological operation

The field of mathematical morphology contributes a wide range of operators to image processing, all based around a few simple mathematical concepts from set theory. The operators are particularly useful for the analysis of binary images and common usages include edge detection, noise removal, image enhancement and image segmentation. Morphological techniques typically probe an image with a small shape or template known as a structuring element. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighborhood of pixels. Morphological operations differ in how they carry out this comparison.

Morphological operation is the important part in image segmentation. By using the imsubtractTop hat and bottom hathas been performed. Subtracting an open image from the original is called a top hattransform. Bottom hat is defined as the closing of the image minus the image.Finally, clean and bwareaopen is used after the rough entropy image**.** Clean in bwmorphremoves pixels individual 1s that are surrounded by 0s.Bwareaopenremoves from a rough entropy image all connected components (objects) that have fewer than P pixels, producing another binary image, BW2.The resultant morphological and rough entropy image is shown in the Figure 6.



(a) (b)

Figure 6. Rough entropy and Morphological operation for a)gray scale image b) green extracted image.

IV. RESULT AND DISCUSSION

A. Performance Error Measure

The segmented image is compared to the manually segmented image based on their performance measures for both the grayscale image and green extracted image. The Probability Rand Index (PRI), Global Consistency Error (GCE), Local Consistency Error (LCE) measures are used for comparison process. The comparison results shows that the segmented image from green extracted image is more similar to the manually segmented image. [8]

B. The Probabilistic Rand Index

The Probabilistic Rand Index (PRI) [Pantofaru2005] counts the fraction of pairs of pixels whose labeling are consistent between the computed segmentation and the ground truth, averaging across multiple ground truth segmentations to account for scale variation in human perception. The first metric evaluation is named Rand index and allows to give the accuracy of the segmentation comparing the Ground-Truth and the segmented image. This measure represents the closeness of the Ground Truth and the segmented image[8,9].The PRI can be calculated in the equation 3.

$$RI(S,S') = 2(n11 + n00)/N(N-1)) \tag{3}$$

Where n11 denotes the numbers of pairs that are in the same cluster under Sand S', n00 denotes the number of pairs that are in different clusters under Sand S'. RI depends on both the number of clusters and the number of elements, and ranges from 0 to 1. S and S' are identical when RI equals to 1.

C. Local And Global Consistency Error (LCE,GCE)

The Local and Global Consistency Error (LCE - GCE) allows to evaluate the dissimilarities between the Ground-Truth and the segmented image and between the segmented image and the Ground-Truth [19].

1) Local Refinement Error:

In order to compute the LCE and GCE, the local refinement error between clusters of the Ground-Truth and the segmented image and between clusters of the segmented image and the Ground-Truth are calculated using the equation 4 and 5.[8,9]

The error is defined as follow:

$$\mathrm{E(GT,S,p_i)} = \frac{|\mathrm{R(GT,p_i)\backslash R(S,p_i)}|}{|\mathrm{R(GT,p_i)}|} \tag{4}$$

$$\mathrm{E(S,GT,pi)} = \frac{|\mathrm{R(S,p_i)\backslash RGT,p_i)}|}{|\mathrm{R(S,p_i)}|} \tag{5}$$

2) Global Consistency Error:

The Global Consistency Error (GCE) [Martin2001] measures the extent to which one segmentation can be viewed as a refinement of the other. Because the GCE is zero for the extreme cases where one image is a single region or every pixel in an image is assigned a unique label, it only makes sense to compare the GCE of images segmented into (almost) the same number of regions. Segmentations which are related in this manner are considered to be consistent, since they could represent the same natural image segmented at different scales [18].The GCE can be calculated using the equation 6.[8,9]

$$GCE(GT,S) = \frac{1}{n} min\{\sum E(GT,S,pi), \sum E(S,GT,pi)\} \tag{6}$$

Where GT is the manually segmented image, S is the rough entropy segmented image and pi is the pixel of the manually segmented image and rough entropy segmented image.

3) Local Consistency Error:

Local consistency error (LCE) forces allow refinement in different direction in different part of the image. Let n be the number of pixel.The GCE can be calculated using the equation 7.

$$LCE(GT,S) = \frac{1}{n}\sum min\{E(GT,S,pi), E(S,GT,pi)\} \quad (7)$$

Where GT is the manually segmented image , S is the rough entropy segmented image and pi is the pixel of the manually segmented image and rough entropy segmented image. The segmentation error takes two input GT and S and produces real value output in the range (0 to 1) where zero signifies no error .It allows to evaluate the dissimilarity between cluster of the segmented image and ground truth image is illustrate in the below table1.

TABLE I. PERFORMANCE ERROR MEASURE FOR GRAY SCALE AND GREEN EXTRACTED IMAGE

	Gray Scale Image				**Green Extracted Image**			
	T1	***T2***	***T3***	***T4***	***T1***	***T2***	***T3***	***T4***
PRI	0.6521	0.6645	0.7066	0.6671	0.6300	0.6250	0.7000	0.6500
GCE	0.3145	0.1915	0.1570	0.4033	0.0392	0.0404	0.0328	0.0395
LCE	0.2141	0.1715	0.1461	0.4031	0.0375	0.0405	0.0378	0.0467

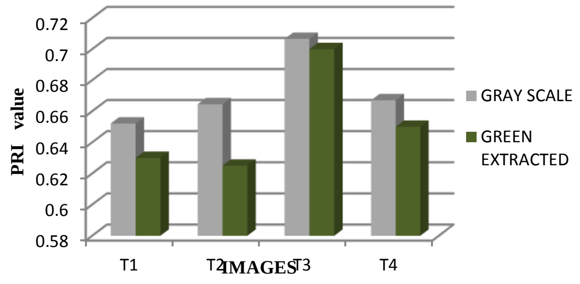


Figure 7. Chart Representation of PRI for gray scale image and green extracted image

The above Figure 7 represents the PRI values of Gray-scale and Green extracted image. It describes the similarity of the segmented image and ground truth image. From this, the green extracted image gives higher performance than gray-scale image. The PRI value should falls between the value 0 to 1.

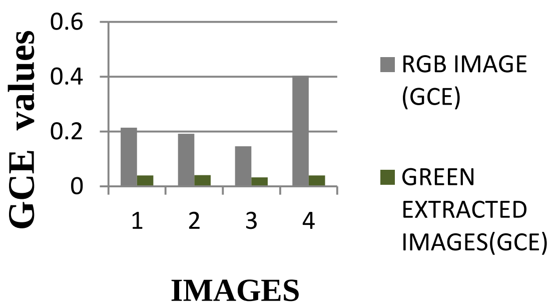


Figure 8. Chart Representation of GCE for gray scale image and green extracted image.

The above Figure 8 represents the GCE values of Gray-scale and Green extracted image. It describes the dissimilarity of the segmented image and ground truth image. From this, the green extracted image gives higher performance than gray-scale image.The GCE value should falls between the values 0 to 1.

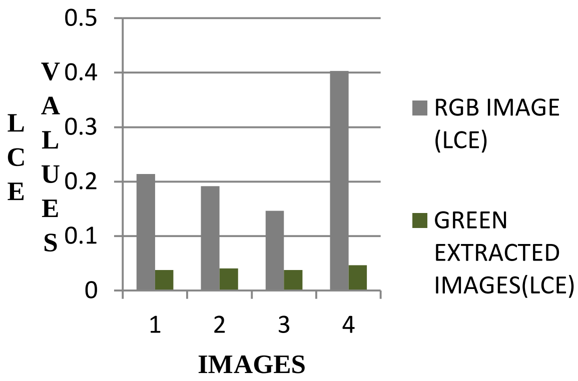


Figure 9. Chart Representation of LCE for gray scale image and green extracted image.

The above Figure.9 represents the LCE values of Gray-scale and Green extracted image. It describes the dissimilarity of the segmented image and ground truth image. From this, the green extracted image gives higher performance than gray-scale image .The LCE value should falls between the value 0 to 1.

V. CONCLUSION

The Hypertensive eye disease is detected by automated process from the retinal blood vessel images. The blood vessels are extracted using Rough Entropy and Morphological method. The proposed method follows various steps from preprocessing to the segmentation of blood vessels. The each step is performed for the betterment of the result. The efficiency of this proposed work is analyzed by comparing it with manual segmentation. The manually segmented image are taken from the DRIVE dataset. The performance measures of both grayscale image and green image is compared. The grayscale image is dissimilar when compared to the manual segmented image. But the green extracted image is more similar when compared to the manual segmented image. The green extracted image provides better result than the gray scale image.

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