Preprocessing and Segmentation of Retina Images for Blood Vessel Extraction

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Abstract. In every field there is use of technology as part of in medical field lot of analysis is done using images. Processing of images will give good analysis when there is no noise or very less noise is present so processing retina images also gives correct results so we used different filters to find out which filter is suitable for pre-processing of retina images available in DRIVE database by computing mean square error (MSE) and Peak signal to noise ratio (PSNR) for different noises. After pre-processing images are segmented using discrete wavelet transform (DWT) and extracted blood vessel pixels are computed and compared with first observer result available in data base and results are very close to manual segmentation which is given DRIVE database.

Keywords: Blood vessels · Pre-processing · Optic disc · Retina image

1 Introduction

Every year the number of people suffering from diabetes is increasing but the medical experts available for correct diagnosis is very less so there need for computerized diagnosis which can reduce the time of experts for detection of diabetic retinopathy. Researchers are worried for the image enhancement since it could be significantly improve the visual perception and as numerical attributes of the image that has a direct impact on the accuracy of analysis by medical experts. To remove noise effects, it is necessary to remove or reduce the noise with preserving image details during the pre-processing that help the correct segmentation of parameters like blood vessels, exudates, optic disc etc which are indicators of diabetic progress in the person. In present work wiener filtering is used as linear filter and median filtering as a non-linear filter. Image Enhancement basically includes noise reduction from the given image can contain noises like Gaussian, salt and pepper.

1.1 Related Work

Retina images acquired by a special camera called "fundus camera" are sometimes low contrast or uneven distribution of light can create strong challenges

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in the process detection of sign of diabetic retinopathy related parameters like blood vessel extraction, optic disc detection, exudates detection and microaneurysm detection etc. which can provide good information about the healthiness of retina. Razban et al. [1], Presented a method for isolating blood vessels from their background content in image acquired by fundus camera that helps in understanding the condition of functioning of retina part of the eye. They used Gabor wavelet to separating background content and mathematical morphology for removing blood vessels. Nisha et al. [2], Proposed a new method that finds the process related to velocity of blood flow in human retina cells which very necessary for providing nutrients to retina cells. This is also called as "major temporal arcade" that helps in detection of blood vessels. In this they used Gabor filter and Hough transform for blood vessel detection. Tejaswi et al. [3], Used matched filter for segmentation of blood vessels from retina images. Neha Gupta and Aarti [4], Implemented a method to detect blood vessels using combination of different filters so as to reduce the possible noise level present in the image and helps for more accurate segmentation of blood vessel network in turn that provide information regarding status of blood vessel functionality. Salazar-Gonzalez et al. [5], Presented a new method called "graph cut technique" for segmentation of blood vascular network from retina image that estimates the location of blood vessels based on graph theory with intensity as a major information source and determined the unusual distribution of small and branched blood veins. Annie Edel Quinn and Gokula Krishnan [6], Developed a method which that uses contrast adjustment over the input image and curvelet transform approach as a next step. They separated green channel from RGB retina image and then contrast adjustment is done over the input image after that curvelet transform is operated to detect edges which form the vessels of retina. Deepa and Mymoon Zuviriya [7], Presented a method for abnormal blood vessel (Thick vessels and extra branches created) detection from retina image using features of Gray level features and moment invariants features and then these features used for classification of pixels belonging blood vessel or not belonging blood vessel. Support vector machine (SVM) is used here as a classifier. Chrastek et al. [8], Segmentation of blood vessels is performed to remove them from retina image later which the optic disc is extracted from retina image captured using fundus camera that provide details required for analysis of retina for determination of diabetes effect. Here blood vessels are separated using "distance map algorithm" and then optic disc is separated using morphological operation, Hough transform and active contour that provide status of optic disc where blood vessels originate in retina. Lowell et al. [9], Segmentation of blood vessels is performed using "template matching algorithm" along with directionally sensitive gradients that is effective in determining blood vessels in different direction throughout the retina which serve as nutrients providing network for retina cells. Welfer et al. [10,11], Extraction of optic disc from retina images is done using adaptive morphological operation and "watershed transform". Here watershed transform is used for marking and detecting optic disc boundary in the retina and morphological operation is used blood vessel segmentation from remaining objects of retina.

2 Proposed Methodology

The algorithm for different preprocessing methods is given below: 1. Read input image. 2. Convert RGB to color. 3. Add different noises to input image. 4. The input become noisy image. 5. Apply different filters. 6. Compute mean square error (MSE) and peak signal to noise ratio (PSNR) for all filters. 7. After pre-processing apply discrete wavelet transform to extract blood vessels. 8. Compute blood vessel pixels and compare with manual segmentation. The processing of images is required to in order to avoid or reduce non-uniform illumination which introduced in process of capturing of retina images. The process of noise removal helps in the task of segmentation of image contents that in turn helps in the process of analysis and makes the image appropriate for automated detection [12,13]. Figure 1 shows the flowchart for proposed work.

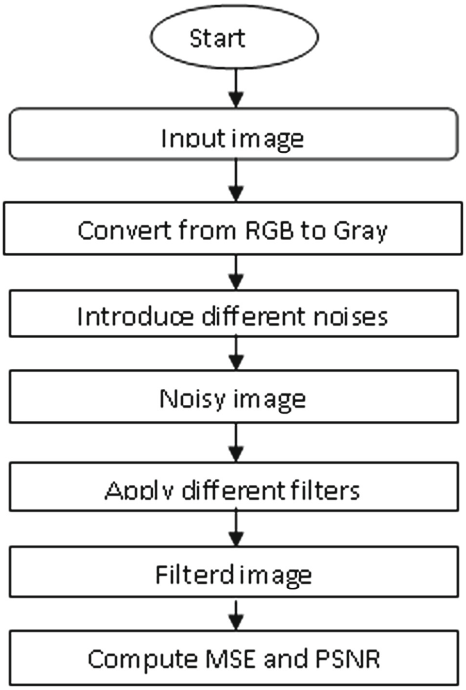

Fig. 1. Flowchart for pre-processing

2.1 Preprocessing Methods

Different filters work effectively on different noises and type of images so it is important to do analysis of filters with different type of images to identify which filter works well for different noise. In this we have considered four noises namely Salt and Pepper noise, Speckle noise, Poisson noise and Gaussian noise. Once pre-processing is carried out its effectiveness is measured listed in Tables 1, 2, 3, 4, and 5 of results and discussion section. It is found that from above tables median filter can suppress the noise from retina images of DRIVE database. Using median filter for preprocessing and discrete wavelet transform (DWT) is used for segmentation the blood vessel pixels are computed tabulated in Table 6.

***A* Filtering:** Filtering of image is performed using different masks with different size like 3×3, 5×5 and with different valued coefficients arranged in various manners. The mask is placed on image such that the center of the mask coincides with first pixel and for median filter all pixels overlapped by mask coefficients are arranged in ascending order and center value is found to be median value then that first pixel is replaced by median value. In next step mask is moved to second pixel in image so that mask center overlaps with it and previous procedure is repeated. This process is performed for all the pixels in the image.

***B* Segmentation:** After an image is preprocessed using median filter segmentation is carried out using mathematical morphology and discrete wavelet and results are tabulated in Table 6.

$$f(n) = \frac{1}{\sqrt{M}} \sum_{k} w_{\phi}(j_0, k) \varphi j_{0,k}\, k(n) + \frac{1}{\sqrt{M}} \sum_{j=j_0}^{\infty} \sum_{k} W_{\psi}(j, k) \psi_{j,k}\,(n) \tag{1}$$

where j_0 is an arbitrary starting scale, and $n = 0, 1, 2, 3 \ldots m$. Approximate coefficients are given by Eq. 2

$$W_{\phi}(j_0, k) = \frac{1}{\sqrt{M}} \sum_{x} f(x) \phi_{j0,k} \tag{2}$$

The detailed coefficients are given by Eq. 3

$$W_{\phi}(j_0, k_0) = \frac{1}{\sqrt{M}} \sum_{x} f(x) \phi_{j0,k\,0}(x) \tag{3}$$

Table 6, shows the comparison of pixels count obtained by segmentation of DRIVE database images using median filtering and segmentation using wavelet transform technique with respect to manual segmentation of DRIVE database images provided with DRIVE as ground truth.

2.2 Performance Measures

For all segmented images how many pixels are belonging to blood vessels and how many pixels are belonging to background is estimated and compared with manual segmented images and their pixels count is considered for performance measurement. Mean Square Error (MSE): Definition: The MSE is the cumulative squared error between the compressed or reconstructed and the original image. In statistics, the mean squared error (MSE) or mean squared deviation

(MSD) of an estimator measures the average of the squares of the errors or deviations - that is, the difference between the estimator and what is estimated. A lower value of MSE means lesser value. Peak Signal to Noise Ratio (PSNR1): Definition: "It is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation or PSNR is a measure of peak error." The Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR) are the two error metrics used to compare image compression quality. The MSE represents the cumulative squared error between the compressed and the original image, where as PSNR represents a measure of the peak error. High PSNR means good image quality and less error introduced to in the image. Once pre-processing is carried out its effectiveness is measured listed in above Tables 1, 2, 3, 4, and 5. It is found that from above tables median filter can sup-press the noise from retina images of DRIVE database. Using median filter for pre-processing and discrete wavelet transform (DWT) is used for segmentation the blood vessel pixels are computed tabulated in Table 6.

3 Results and Discussion

The pre-processing of retina images helps in segmentation of images that leads to extraction of diabetic characteristics from available database images. The results obtained by the proposed methodology shows that the median filter is good preprocessing filter for DRIVE database images since it produces results our experiments, with known number of images in each category and number of category in the database. Table 6 shows the comparison of percentage of pixels classified as blood vessel pixels and percentage of pixels classified as non blood vessel pixels that indicates accuracy of segmentation process .

Table 1. MSE and PSNR values for mean filter

Sl. No	Types of noise image	Average MSE	Average PSNR
1	Salt and pepper noise	7.6504	36.90
2	Speckle noise	9.6207	35.96
3	Poisson noise	8.9772	39.78
4	Gaussian noise	11.187	32.99

Table 2. MSE and PSNR values for median filter

Sl. No	Types of noise image	Average MSE	Average PSNR
1	Salt and pepper noise	6.6504	39.90
2	Speckle noise	6.6207	39.96
3	Poisson noise	6.9772	39.78
4	Gaussian noise	6.187	39.99

Table 3. MSE and PSNR values for arithmetic mean filter

Sl. No	Types of noise image	Average MSE	Average PSNR
1	Salt and pepper noise	39.45	43.98
2	Speckle noise	36.83	46.30
3	Poisson noise	36.68	38.99
4	Gaussian noise	38.11	36.59

Table 4. MSE and PSNR values for SVD decomposition filter

Sl. No	Types of noise image	Average MSE	Average PSNR
1	Salt and pepper noise	121.6959	27.72
2	Speckle noise	122.74	26.07
3	Poisson noise	122.81	27.366
4	Gaussian noise	118.67	27.12

Table 5. MSE and PSNR values for weighted mean filter

Sl. No	Types of noise image	Average MSE	Average PSNR
1	Salt and pepper noise	97.99	28.38
2	Speckle noise	98.44	28.49
3	Poisson noise	99.24	29.41
4	Gaussian noise	95.42	28.42

Table 6. Comparison of extracted blood vessel pixels by proposed method and manual segmentation.

Test images (DRIVE DB)	No. of pixels obtained	No. of pixels (1st observer or manual)	Diff. in percentage
Image1	41220	38419	7.2
Image2	42135	38457	9.41
Image3	47056	38480	22.23
Image4	39344	38514	2.14
Image5	36061	38480	6.28
Image6	39812	38501	3.40
Image7	42811	38404	11.41
Image8	48020	38429	24.91
Image9	41351	38470	7.41
Image10	30674	38463	20.20
Image11	39879	38460	3.61

(*continued*)

Table 6. (*continued*)

Test images (DRIVE DB)	No. of pixels obtained	No. of pixels (1st observer or manual)	Diff. in percentage
Image12	43155	38458	12.21
Image13	33769	38448	12.15
Image14	43779	38421	13.91
Image15	39596	38410	3.01
Image16	37434	38481	2.72
Image17	44873	38414	16.80
Image18	37618	38434	0.47
Image19	38036	38461	1.10
Image20	38130	38414	0.71

4 Conclusion

In this paper pre-processing of retina images to help in segmentation is presented, segmentation of images that leads to extraction of diabetic characteristics from available database. The results obtained by the proposed methodology shows that the median filter gives good pre-processing for DRIVE database since it produced low value of mean square error and high peak signal to noise ratio. We have made an attempt to study image enhancement by using linear and non linear filtering technique. Also salt and pepper noise and Gaussian noise added into image after applying median filtered, it was observed that salt and pepper noise and Gaussian noise reduction was better than wiener filter. The median filter perform better than wiener filter, it is not only better for noise reduction also remove the blurred effect in image After pre-processing the blood vessels are segmented and extracted blood veins pixels are counted they shows the result which is very close to manual segmentation process which is available in DRIVE database.

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