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An Enhanced Method for Retinal Image Analysis Using Image Processing Techniques

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ABSTRACT
A wide-ranging, routine screening of the enormous numbers of potential ocular patients is made possible by automatic retinal screening systems (ARSS), which only offer professional treatment when early disease signs are identified. Serious vision impairments brought on by extensive disease progressions of silent retinal illnesses, such as diabetic retinopathy, can be avoided or delayed with early identification and appropriate treatment. However, it was discovered that the calibre of the retinal pictures that were processed had a significant impact on how reliable these systems were. This thesis presents a no-reference comprehensive wavelet-based retinal image quality assessment (RIQA) method for ARSS-based early detection of diabetic retinopathy.
Keywords : Automated Retinal Screening Systems, Retinal Picture Quality Evaluation, And Biomedical Imaging.

I. INTRODUCTION

Recently, conducting polymer, Polypyrrole (PPy) have been used as sensitive material for the development of gas sensors [1-9]. Chemical polymerization is the simple method to synthesize the PPy film [10-15] It is easy technique and can be controlled by suitable process parameters. The synthesized thin film found to be porous, stable, sensitive, and gives significant change in resistivity when exposed to ammonia gas [16-18]. Monomer Pyrrole (Py), dopant Acrylic Acid (AA) and oxidant ferric chloride ($FeCl_3$) have been used for chemical polymerization of PPy at room temperature and optimized the process parameters [19,20] These synthesized PPy-AA films on PMMA substrate were characterized by FTIR, scanning electron microscopy (SEM), ultraviolet-visible (UV-vis) spectroscopy. The sensitivity of the film to ammonia gas was studied by indigenously developed sensing chamber (Figure 1) in the laboratory [21-23].

II. EXPERIMENTAL

Then, retinal pictures are obtained by a non-invasive technique that entails employing specialised digital fundus cameras to capture the light reflected from the retina. The OD, the macula area, and the blood vessels are among the most significant features of the retina as shown in Figure 1.1. The macula is the dark area in the centre of the retina that is situated to the side of the OD, whereas the OD is the circular section of the retina that is brightly lighted.

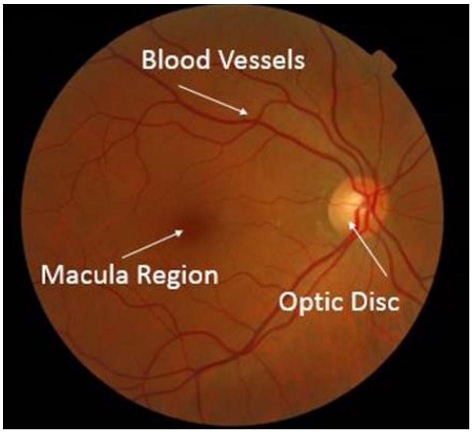


Figure 1.1: Example of retinal image from MESSIDOR

The well-known idea that retinal pictures include overexposed red channels, high contrast green channels, and dark blue channels is therefore clearly explained by the RTM. Red, green, and blue channels for a retinal picture are displayed in Figure 1.2. The green channel of the retinal picture is the most often employed channel in image processing methods including quality evaluation, augmentation, and vessel segmentation because of its great contrast.

Figure 1.2: Red, green and blue colour channels from a colour retinal image from DRIMDB

III. LITERATURE REVIEW

Spatial RIQA techniques can be further divided into generic and segmentation-based approaches. Generic RIQA approaches tend to rely on general features that do not take into account the retinal structures within the images. In early literature, Lee et al. [1] compared the test image's histogram to a template histogram created from a group of high quality retinal images for quality assessment. Shortly after, Lalonde et al. [2] argued that good quality retinal images do not necessarily have similar histograms and proposed using template edge-histograms instead. Nevertheless, both these approaches depended on templates created from a small set of excellent retinal images which do not sufficiently consider the natural variance in retinal images.

Recently, generic approaches evolved to use a combination of sharpness, textural, and statistical features to evaluate retinal image quality. Davis et al. [3] calculated different Haralick measures (entropy and contrast) [4], statistical features (mean, variance, kurtosis, skewness, first quartile (Q1) and third quartile (Q3)) along with spatial frequency to completely characterize the luminance and sharpness of retinal images computed from seven local regions covering the entire retinal image. Fasih et al. [49] combined cumulative probability of blur detection (CPBD) [5] along with Run Length Matrix (RLM) features [6] for quality evaluation calculated from the macula and OD regions. Dias et al. [7] assessed retinal image quality based on four quality issues namely focus, contrast, illumination, and color based on gradient map and statistical features.

IV. FORMULATION OF PROBLEM

Recently, RIQA algorithms have started using transform-based techniques. The multiresolution characteristics of WTs or the existing wavelet-based RIQA techniques, however, are not completely used by these algorithms. Relationship between the various wavelet levels and the retinal architecture. The five level detail sub bands of retinal pictures are utilized to compute wavelet-based sharpness characteristics.

Additionally, a thorough analysis is done to assess the importance of global and local features as well as to choose the wavelet level best suited for feature computation. Two datasets with various resolutions and quality levels are used to evaluate the suggested wavelet-based features. The provided algorithm's classification performance and calculation times are then compared to a number of published RIQA approaches. Due of its high contrast, RIQA algorithms frequently solely employ the green channel for feature calculation. However, the overall sharpness of the picture can also have an impact on how visible the retinal structures are in the red channel.

As a result, the red and green detail sub bands of the retinal pictures were used to determine the added sharpness and contrast properties.

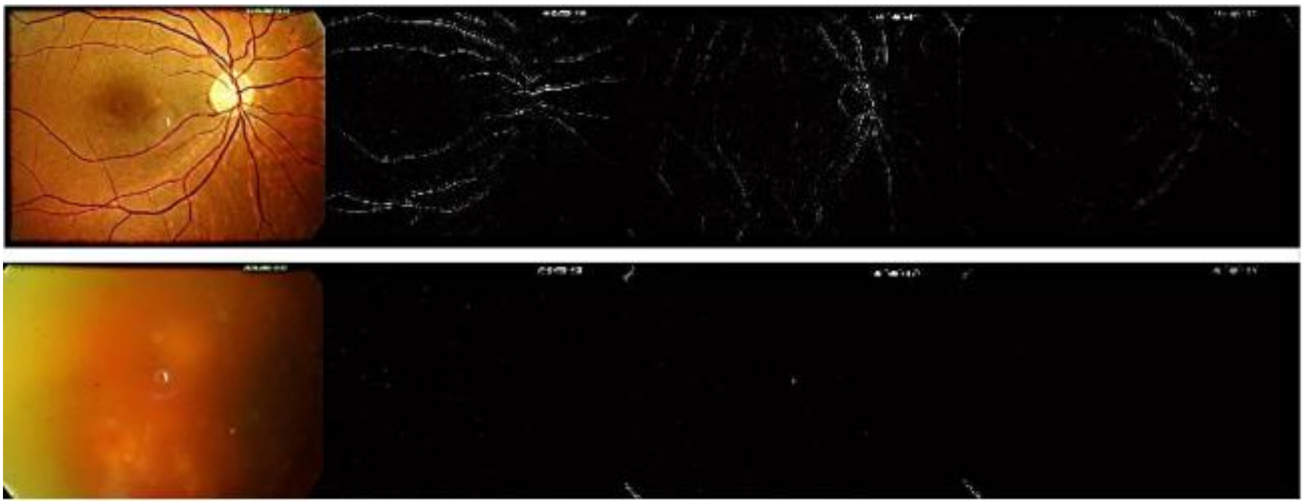
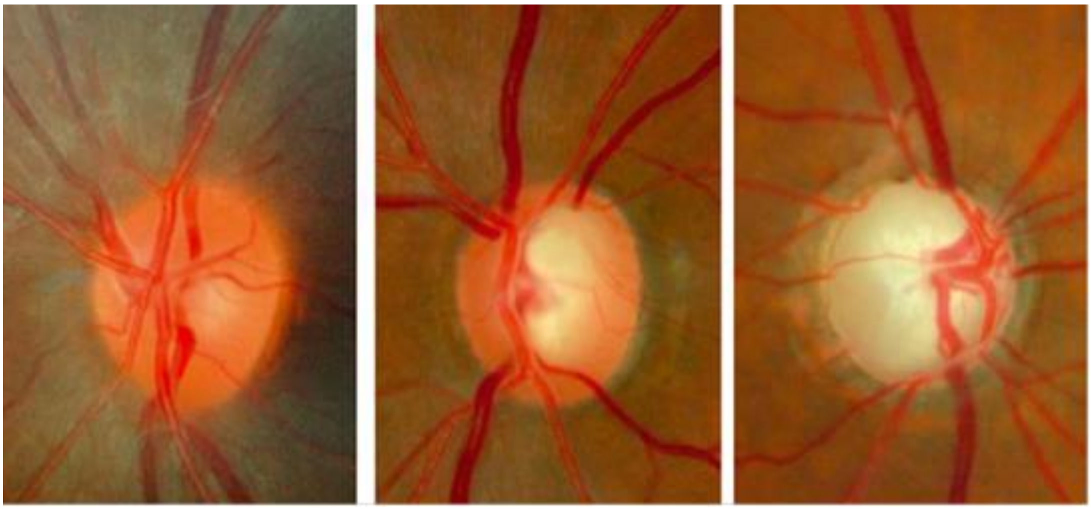


Figure 3.1 : Level 2 green channel detail sub bands of retinal images from the DRIMDB that are crisp (first row) and fuzzy (second row).



(a) (b) (c)

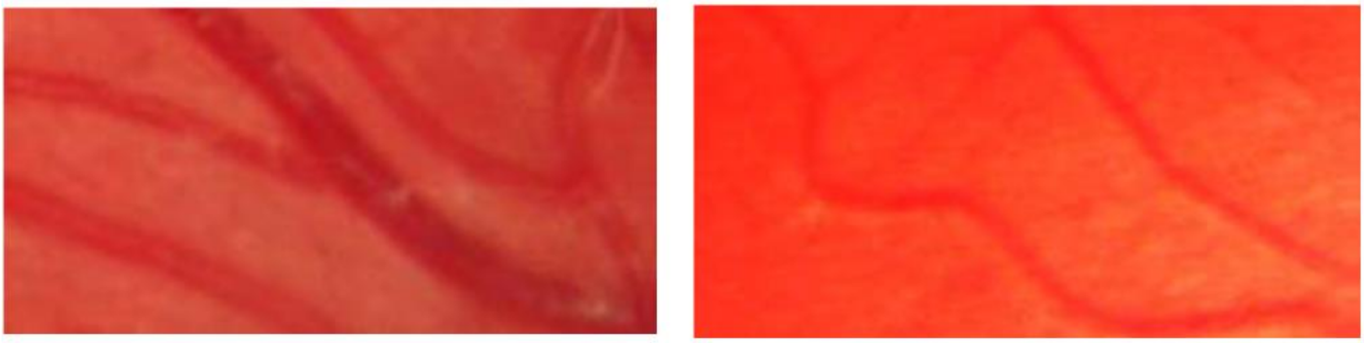
Figure 3.2 Examples of (a) normal ODs and (b,c) glaucoma ODs with varying disease severity

V. METHODOLOGY

The most pertinent wavelet level for RIQA feature calculation is found by wavelet level analysis. Nirmala et al.'s research has demonstrated a connection between the various wavelet levels and the blood vessels in the retina. This approach was re-implemented in this chapter to determine the most significant wavelet level to be used to the calculation of features. Small parts of various retinal pictures with either thick or thin vasculature were removed, and the coefficients of the following detail sub bands were set to zero.

Then, to determine which wavelet level has the most impact on the retinal vasculature, the mean SSIM was computed to evaluate similarities between original and zeroed sub bands.

To verify the outcomes of the earlier investigation, a second experiment was also carried out. Results from the various levels were compared, and the provided sharpness and contrast attributes from the individual wavelet level were used for categorization.



(a) (b)

Figure 4.1: Examples of (a) thick and (b) thin retinal vessels from HRF

This region is defined by dividing the image horizontally into four equal sections then regarding the two middle sections together as the center region. The choice of a relatively wide center region allows taking into account any slight vertical shift in the macula centered retinal image. Figure 4.1 illustrates the local region defined in this chapter.

Figure 4.2: Retinal image showing local region

Figure 4.3 : Outlier images from DRIMDB

VI.RESULTS

Five wavelet levels of the red and green channels were used to calculate the newly announced wavelet-based RIQA characteristics. For retinal image decomposition, the Daubechies4 "db4" wavelet was selected since it has been effectively applied in several retinal image analyses in the literature. Furthermore, compared to the straightforward wavelet, which utilizes non-overlapping windows, the db4 wavelet adapts overlapping windows, which better captures edge information inside pictures.

The most pertinent wavelet level and feature type (local or global) to be employed in the final classifications were determined by integrating the findings of the two feature analyses. The k-nearest neighbor classifier was used for the studies since it can be readily modified and has been proven to produce reliable findings. The k parameter was changed in each KNN classification experiment to a value between 1 and 10, and the best classification outcomes were reported. A support vector machine classifier with a radial basis function kernel tailored to get the best results was used to make the final classifications. The Weka platform was used to produce 10 fold cross validation classification findings, while all features were calculated using MATLAB .

VII. CONCLUSION

The analysis and classification findings for the suggested RIQA measures are reported in this section. Sharpness, illumination, homogeneity, field definition, and outliers are the first five feature sets that are analyzed individually. The DR1 dataset, which contains more than 2690 retinal pictures with varying quality concerns, is then classified using the final quality feature vector that has been created.

Finally, the suggested RIQA algorithm's overall quality results are contrasted with those of existing algorithms from the literature.

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