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"Subjective Evaluation of Fund us Images of Human Eye"

[1] Jalendra H V [2] Veena S K
[1][2]Department of Electronics and Communication,
Maharaja Institute of Technology Mysore, Karnataka, India

***Abstract*— Fund us pictures of the human eye are used by Ophthalmologist to analyze and screen the diseases like glaucoma or diabetic retinopathy. To evaluate Fund us images captured from camera before sending to the doctor for analysis and patient diagnosis is very important. The Fund us images are checked for basic quality parameters like availability of Optic Disk, Blood Vessels, and Optic Cup as high priority and Brightness Contrast, Illuminations and Signal to Noise Ratio etc. as a second level check. Qualified Fund us images are trained using Support vector machine for good and bad quality by methods of Clustering, Heraldic features and Sharpness. Subject image is compared with Trained data for Good and Bad quality.**

***Keywords*- Retina scan, Fund us image, quality assessment of Fund us image, non-reference image quality metric**

I. INTRODUCTION

The human eye is a vital organ that acts to luminous and has distinct view. Rod and cones in the retina allow concise light sense and view, inclusive of color differentiation and the field of measure. The eye can differentiate about 10 million colors. As the eye act as key part in the human system and it has to be precisely cared. India has an approximated over 25% of 45 million cases around the world. 80% of those instances of ordered deformity are stoppable. Fund us Images are the key part in analysis and patient diagnosis for diseases. Diabetic retinopathy, waterfall, glaucoma and cornea issues sanction 90% of visual deformity[16].

Design of advanced tools can be more analytical with a significant measure of quality (contrast, sharpness, Illumination etc.) than by biased comparison. In the field of active computerized decision of 'not good enough' can produce a live re-take, with no need for a new appointment.

I.1 Problem Statement:

As we all know, Medical images plays key role in analysis and patient diagnosis. Particularly in ophthalmology images of the human eye in hospital are utilized by ophthalmologist for analyzing and screening the ailment like glaucoma or diabetic retinopathy. Also the medical images are normally prepared via programmed devices to improve the analysis. Ophthalmologist require certain condition of image quality to guarantee a dependable finding and a legitimate robotized preparing. In view of the working individual's diverse levels of experience, particular sorts of capturing device or the individual characteristics of the obtained eye the nature of images exceedingly fluctuates. However in the present world it's difficult for the people to come again for reacquisition as it again time engrossing and also the cost of acquisition will be extravagant. It depends upon different individual perspective at which the image quality is judged either it can be valuable or poor for stable diagnosis. Henceforth a strong evaluation of the image during acquisition is required. This would be further helpful to protect the overall quality and stable diagnosis.

I.2 Literature survey:

In literature, the main intention for quality evaluation in common images is to compare original images to their subject image captured from Fund us camera for quality loss quantification, so called reference approaches. Es- kicioglu et al. [5] gives a survey of crucial quality estimations for this issue, such as average difference cross-correlation or normalized cross-correlation. Many works in that field develop extended approaches [6] e.g. driven by the human eye's function of finding structures [7]. Despite of the importance of this problem it is still a widely neglected field of research especially with regard to ophthalmic Fund us imaging [15]. There are only few relevant publications on retinal image quality assessment: (i) Segmentation based approaches detecting anatomical structures and also the same way segmentation will fail on low quality medical images due to the bad reading and recognizability. Fleming et al. [8] measure the quality by evaluating the vessel structures of main branching, second level and third level branching in the

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region around the macula and Optic Disc. Giancardo et al. [9] measure the densities of vessels for different regions in the image. (ii) Histogram based approaches use information picked up by image measurements to recognize low quality photos. Reference histograms are calculated out of images showing good quality and cross checked and verified with the input image's histograms for classification. Lee et al. [11] compute a quality index by convolving the image intensity histogram of the input image with the template intensity histogram from good Fund us images. Image Structure Clustering [12] characterizes the image quality by the distribution of image intensities itself and the capacity to group the image into the contained anatomical structures. Five clusters are calculated from the input image using a bank of filters to transform the pixels into the gauge coordinate system that is defined at each point by the direction of its gradients.

II. METHODOLOGY

Reference Image Quality Flow**:** Figure shows the steps carried out on training images for Quality

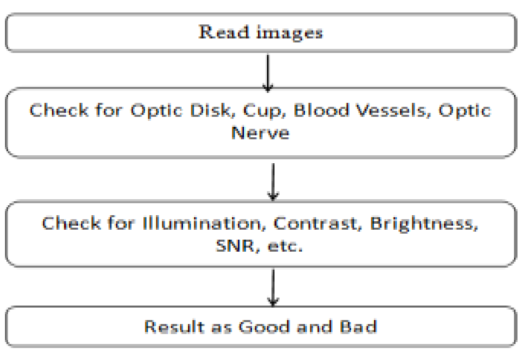


Fig 2.1 Flow diagram of Reference Image Qulaity check

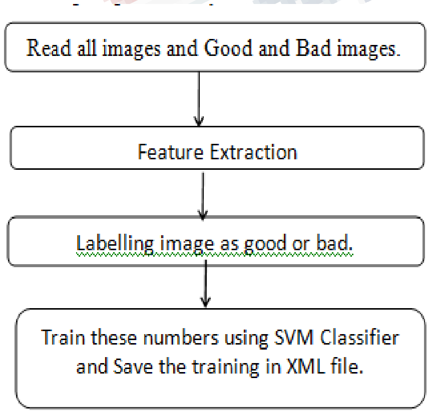


Fig 2.2 Flow diagram of Image Quality Training

Quality Testing Flow: Figure shows the steps carried out on testing images for Quality

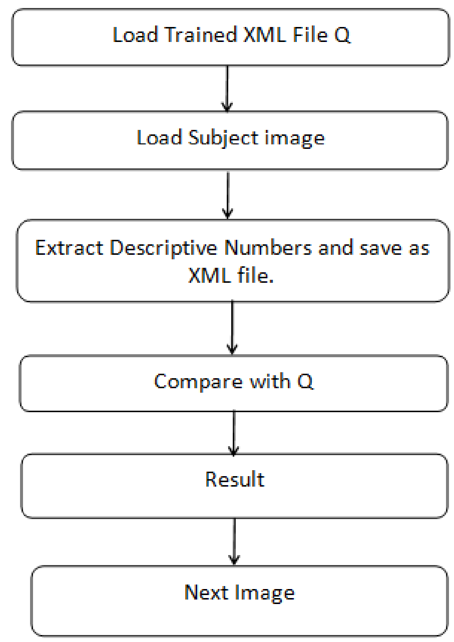


Fig 2.3 Flow diagram of Image Quality Training

Fig 2.1: Retinal Image

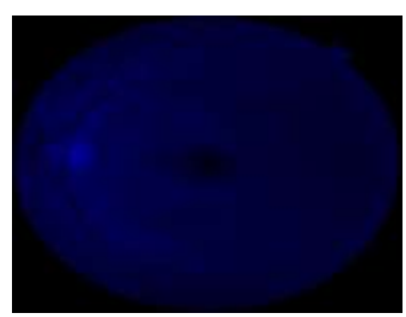


Fig 2.1.1: Blue Channel Retinal Image

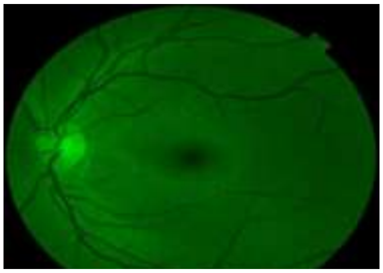


Fig 2.1.2: Green Channel Retinal Image

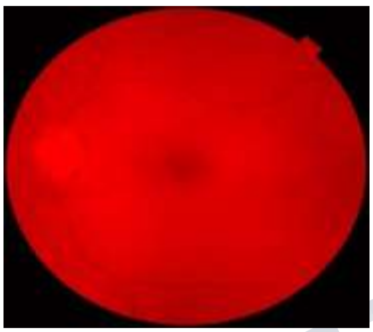


Fig 2.1.3: Red Channel Retinal Image

2.1 Top approach

For reference image quality top approach is used. Optic disk is identifef using threshold method, counting vessels structures by canny edge detection method , maximum threshold method for finding the optic cup.

1. Conversion of RGB to YCbCr
2. Threshold applied to Cb component
3. For Disc threshold is set to >120;
   Disc=b(:,:,1)>120;
4. For Cup threshold is set to >160;
   Cup=b(:,:,1)>160;
5. Edge detection using canny filter for vessels counts.

2.2 Second level approach

Second level approach is used for finding the Illumination, Brightness, Contrast and Signal to noise ratio.

Illumination using variance method using reference set of images qualified by Doctors.

- Standard deviation
- variance methods

Brightness with mean intensities using reference set of images

- Brightness =Mean2(image)

Contrast using Average of maximum and minimum brightness using reference set of images qualified by Doctors.

- Contrast =Avg(max-min)

SNR-Signal to noise ratio id found using

- SNR-Signal to noise ratio =10log10(Signal/Noise)

Training method consists of a clustering, a sharpness metric and Haralick texture Features. Combining all features in one final vector. For all Computations only *the green channel was considered as it shows the best contrast*[15].

2.3 Clustering:

It is a work of categorization a group of identical substance in a look-like group. Cluster analysis itself is not one definite algorithm, but the familiar work to be solved.

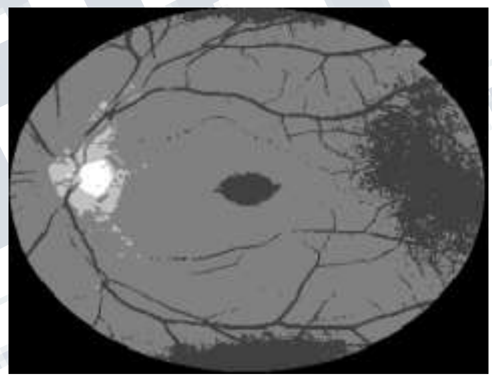


Fig 2.3.1: Retinal Cluster Image

As proposed method want to assure sufficient recognizability and differentiation of anatomical structures identify these components by applying a K-Means-clustering of the input image I of size nxm with k clusters Ci with i Ɛ{1…k}. The gray values g_{xy} with x Ɛ{1…n} and y Ɛ{1…m} are grouped in clusters without further preprocessing. The clustering centers are initialized with mean values of the k structures (e.g. vessels) in 10 images manually segmented by one person. Cluster center are arraanged in ascending order. In each image representative pixels for each cluster were identified and their intensities averaged for each cluster over all 10 images[15]. In good quality images each anatomical structure has an expected size where significant variations refer to bad recognizability and thus bad quality in Fund us image. Proposed method assess cluster structure size by using the normalized cluster sizes c_i as features, where # denotes the cardinal number[15].

$$c_i = \frac{\#\{g_{xy}|g_{xy} \in C_i\}}{} \quad (1)$$

The clearer proposed method can recognize certain structures and differentiate between each component in inter-cluter-contrast. Proposed method use inter-clustering-differences as essential features to express image structural contrast. They are generated by computing the difference d_{ij} between the mean value m_i of a certain cluster C_i and all other clusters' mean values m_j.

$$d_{ij} = m_i - m_j, i \in \{1, \ldots, k\}, j \in \{1, \ldots, k\}, i > j \quad (2)$$

Thus the size of cluster c_i and their inter cluster differences d_{ij} gives the structural recognizability and dissimilarity of relevant image components.

2.4 Sharpness:

Incorporating a sharpness metric that evaluates the edge strength in the image. High gradients identifying sharp edges calculate the gradient magnitude G of the input image I by combining the derivative Ix in x-direction and derivative Iy in y-direction in the Euclidean norm. The gray values e_{xy} in the gradient magnitude picture G are standardized to the range α [0; 1] by a minimum maximum scaling.

$$G = \sqrt{I_x^2 + I_y^2} \ with \ I_x = \frac{\partial I}{\partial x}, I_y = \frac{\partial I}{\partial y} \quad (3)$$

Proposed system use the number of pixels identifying strong edges s1 and the average strength of strong edges s2 to express the image sharpness. Strong edges have to lie above a threshold α [0; 1], that was empirically set to twice the mean gray value in G.

$$s_1 = \frac{\#\{e_{xy}|e_{xy} \geq \alpha\}}{n \cdot m} \quad (4)$$

$$s_2 = \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} v_{ij}}{\#\{e_{xy}|e_{xy} \geq \alpha\}}, \ v_{ij} = \begin{cases} 0 & e_{ij} < \alpha \\ e_{ij} & e_{ij} \geq \alpha \end{cases} \quad (5)$$

$$\alpha = \frac{2 \sum_{i=1}^{n} \sum_{j=1}^{m} e_{ij}}{n \cdot m} \quad (6)$$

Thus both features s1 and s2 indicate how clearly the structures are separated from each other.

2.5 Haralick:

To incorporate generic image quality statistics compute three Haralick metrics [13] that are well known as texture metrics. Proposed system uses entropy h1 as description for common image sharpness, energy h2 as description for image homogeneity and contrast h3. Final Haralick features h1, h2 and h3 are generatedby computing the mean.

2.5 Feature Composition:

For Training uses clustring, sharpness and haralick methods the k cluster sizes c_i, the inter-cluster-differences d_{ij}, the two sharpness metrics s1, s2 and the Haralick features h1, h2 and h3 are combined in one final feature vector. After evaluating the classification performance, choosing k = 5 The gained 20-dimensional feature vector is directly used for classication.

III. MATERIALS AND RESULTS

3.1 Materials

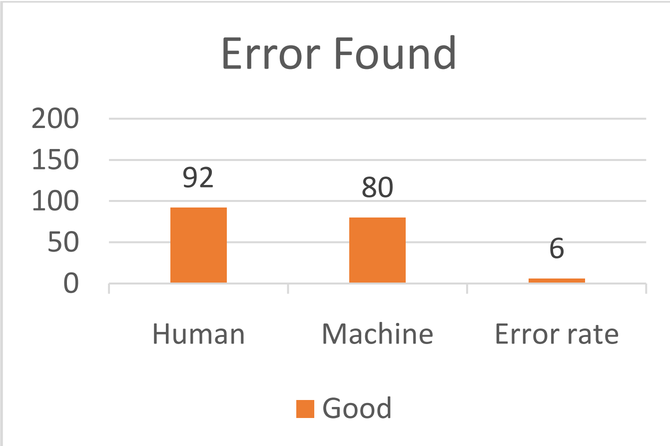
Data set is consisted of 200 retinal color Fund us photos acquired with IDS/Sony 3Mp Camera. The images of size of 1600 x 1212 pixels with a field of view (FOV) of 22:5◦.. For each image the label is classified by the majority of the three observers was defined as an overall quality standard and Using Top and second level approach. In this manner the data set was divided into good and bad Fund us photos.

3..2 Class File Setup

1. Obtain the cluster peaks by K-means clustering Process.
2. Sort successive peaks in ascending order.
3. Estimate the Sharpness of the image using Gradients.
4. Find the Haralicks.
5. Feature Composition of all the above features.
6. Traing using SvmTrain the above features.
7. Compare subject image with tranined data set.

3.2 Results:

The method uses 200 images containing both good and bad images. As 200 images are checked both th Human and Machine approach. Human Approach resulted in 92 good, but same set is checked with machine approach resulted in 80 images were found good. Totally 6 percentage improvemene is seen compared to Human approach.



	Human Approach	Machine Approach
Focus	92 images good	80 images good
Glare	92 images good	80 images good
Ring	92 images good	80 images good
The above results shows for 200 dataset		

IV. CONCLUSIONS:

The proposed criteria by diagnosis procedures based on the advise of an eye experts and specilists help to describe image quality objectively in the application of ophthalmology. Method models these criteria by the use of First level approach for ensuring basic retinal image charecterstics, Second level approach for Uniform illumination with low noise and with proper brightness and contrast. For training clustering, sharpness and Haralick features are used. The proposed method could show that the combination of local and global image statistics produces reliable and robust results in determining the image quality of retinal Fund us photos and increases the sensitivity. Proposed method is closer to a human decision than other approaches. But in particular at the class border the discrimination of good and bad images remains a crucial task. proposed method can substitute an human quality evaluation by the fast objective measurement presented here to ensure a sufficient image quality level in broad screening applications.

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