Abnormality Detection in Automated Mass Screening System of Diabetic Retinopathy

Gang Luo, Opas Chutatape, Shankar. M. Krishnan
School of EEE, Nanyang Technological University, Singapore 639798

Abstract
An approach of abnormality detection from color fundus images for automated mass screening system is proposed in this paper, which uses the object-based color difference image. Four color models, i.e. RGB, Luv, Lab and HVC are evaluated based on the hand labeled feature maps, and Luv and Lab are selected for computing color difference because of their good performance of object classification. The object-based color difference image of bright objects, e.g. exudates and drusen and dark objects, e.g. hemorrhages and blood vessel are obtained respectively according to the 2D histogram distribution on L-u plane, and then watershed transform is performed on the color difference image to extract objects. A pre-thresholding and a post-verification procedures are used to deal with the over-segmentation problem of watershed transform.

Keywords— fundus image, diabetic retinopathy, abnormality detection, color difference, watershed.

1. Introduction
Diabetic retinopathy is a common cause of visual loss in the world. According to the report of the National Institute of Diabetes & Digestive & Kidney Diseases, there are 15.7 millions people, 5.9 percent of the population with diabetes in USA, and the diabetic retinopathy causes from 12,000 to 24,000 new cases of blindness each year. To prevent the progression of the retinopathy or blindness, some grading systems and classifications of diabetic retinopathy have been proposed to assess the severity[1][2].

Digital image processing techniques can help to extract the location and size/level of abnormalities, give an objective grade and compare the changes in objects in sequential images. Although it is far from the real capability of an ophthalmologist, it could still be possible to develop a system to deal with the expensive and time consuming manual process. This system can make an initial diagnosis based on the retinopathy grading criteria by comparing images, measuring key features, annotating image contents, and then select the undiagnosed people in high risk [3].

Abnormality detection is the first step in an automated screening system before making diagnosis. Based on the grading criteria proposed by the ETDRS (Early Treatment Diabetic Retinopathy Study) group of Fundus Photograph Reading Center, University of Wisconsin, the abnormalities can be divided into three classes as follows from the angle of image processing.

Abnormal spot class: microaneurysms, hemorrhages, drusen, hard exudates, soft exudates, vitreous hemorrhage, scars of prior photocoagulation, etc.
Abnormal blood vessel class: intraretinal microvascular abnormalities, venous abnormalities, arteriolar abnormalities, arteriovenous nicking, new vessel, dilated tips of new vessels elsewhere, papillary swelling, etc.
Abnormal stereo measurement: plane of proliferation elsewhere, retina elevation, retinal thickening, etc.

The abnormalities of first class can be detected based on their color and shape. The second class can be extracted by blood vessel detection techniques, which have been studied by
many researchers for years in cardiology as well as ophthalmology. Some successful techniques of vessel detection have been developed [4][5][6]. For the third class, the stereo reconstruction techniques are needed to do the measurement, which can give accurate and objective evaluation. This paper focuses on the detection of the first abnormalities class.

2. Color model selection

In fundus images, the obvious normal physiological structures include optic disc, blood vessel and macula. Along with the abnormal objects of first class, the visible objects can be divided into white or yellowish objects and dark or reddish objects. Image background, whose color is medium, can be considered as the third object. In this paper, the detection of these objects is based on their color rather than just intensity or any single color component. The exact color of an object can be represented with several color models but their suitabilities for image processing must be evaluated in order to find out an optimized one for recognizing the objects in fundus images. In this paper, Red-Green-Blue (RGB), CIELAB, CIELUV and HVC color models are assessed.

Firstly, the white objects (said \(F_1\) here) and dark objects (said \(F_2\)) of the samples of fundus image are hand-labeled respectively. Secondly, each pixel of the images is tagged with one of the three objects, white, dark and background objects (said \(F_3\)) according to the hand-labeled figure. Finally, the maximum sensitivity corresponding to every color component is obtained by scanning the color coordinate and finding the optimized threshold.

Because the fundus is not a plane (spherical face), the illumination is uneven. The brightness of objects and background in central region is usually higher than that in surrounding region, and the color of background in central region may be brighter than the color of exudates in the surrounding region. In order to deal with the uneven illumination, the fundus images are divided into small blocks and the images are analyzed blockwise in color model assessment as well as abnormality detection. The block size is 64 by 64 in this paper.

In total 180 blocks were analyzed. The results are shown in Fig. 1. It can be seen that Lab-a or Luv-u has high sensitivity and equal performance for \(F_1\), \(F_2\) and \(F_3\). RGB-g also has good performance but the distribution of object colors in RGB space does not follow a clear and fixed pattern, unlike in Luv or Lab space as described in next section. Therefore, CIELUV and CIELAB are selected as the color space for image processing. They are perceptually uniform color models recommended by CIE and the color difference measured in these color spaces is close to that of human perception. This will help enabling the diagnosis software to have a similar color perception to doctors.

![Fig. 1. Sensitivity of different color components for object classification](image-url)
3. Abnormality detection

3.1. Object based color difference image

Fig. 2 shows the two contour maps of 3-D histogram of one block of a fundus image in Luv color space plotted on L-u and L-v planes. After a number of careful observations, it is found that the histogram distributions of all blocks follow three common patterns as follows.

- The high region corresponds to the background except the special case mentioned in the next paragraph.
- In L-u figure, the northwest quadrant relative to high region corresponds to the bright objects such as optic disc, exudates and drusen.
- In L-u figure, the southeast quadrant relative to high region corresponds to the dark objects such as hemorrhages and blood vessels.
- It is difficult to discriminate objects along the v color coordinate. Therefore v color component is not used in the object detection.

The color coordinate of background is different from block to block because of the uneven illumination. For most image blocks the background can be located correctly by finding the high region in L-u histogram figure, but for some blocks in which bright objects (usually optic disc) occupy the major area the criteria of finding high region will fail. Therefore, the lightness of background obtained by this method should be checked by comparing with the background surrounding it. Fig. 3 shows the lightness array of high region of a fundus image blockwise. Obviously, the value of a block on left side is quite different from the others, which is due to optic disc. In this case, the lightness of high region is not of background so the background of this block is replaced with that of block beside it.

After the background is identified, a round region centered at the histogram peak is delimited as the background candidate. The northwest quadrant outside this region is treated as the bright object candidate and the southeast quadrant, the dark object candidate. For each of candidates of bright object region and dark region, the location of gravity center is calculated as the reference color of the object with following equation.

\[
L_i = \text{average}\left(\sum L_i \times h(L_i, u_i)\right)
\]

\[
u_i = \text{average}\left(\sum u_i \times h(L_i, u_i)\right) \quad (L_i, u_i) \subset \text{object region}
\]

The star and circle symbol in Fig. 2 indicate the reference colors of bright object region and dark object region respectively.
The object based color difference image of an object is generated by computing the color difference between the object reference color and the color of all image pixels with following equation.

\[ D_{i,j} = \sqrt{(L_{i,j} - L_r)^2 + (u_{i,j} - u_r)^2} \]

Fig. 4 shows the color difference images of bright object and dark object, in which objects appear as dark pixels. The blank block means that there is no object candidate found in that block.

![Fig. 4. Object based color difference images— bright objects (a) and dark objects (b). Dark spots correspond to objects.](image)

### 3.2. Object detection

The object detection is also performed blockwise. The basic approach is to detect spot object with watershed transform of gradient modification [7][8]. The watershed transform is a very sensitive detection method whose one common problem is over-segmentation. It is partly due to noise but in many cases it is caused by some irrelevant objects or some minor patterns. In this paper, a pre-thresholding and a post-verification procedures are used to deal with the over-segmentation problem. The detection procedure is as follows.

A. De-noising by filtering the image with close and open alternating sequential filters. A structuring element of 3 by 3 cross is used.

B. Obtaining inner markers by detecting the regional minima of image, and then obtaining the watersheds of filtered image using the inner markers to be the outer markers. A thresholding is performed before marker detection in order to avoid the minima in non-feature regions to be extracted, e.g. background. All the pixels whose value is larger than the threshold are set to be maximum pixel value. The threshold is obtained according to the histogram of the color difference image (Fig. 5). As the peak usually corresponds to the background, the threshold is set at the maximum differential point at the left side of peak. For the blocks that feature object occupy major area as mentioned above, the peak corresponds to the object. In such case, the threshold is set at the peak point. The threshold does not need to be accurate because it is not for segmentation but for obtaining markers.

C. Performing watershed transform on the morphologic gradient image superimposed by inner markers and outer markers (Fig. 6b).

D. Verifying watershed results by dilating the watershed contour and then checking the difference between the mean of the pixel values along the inner contour and that along the outer contour. If the difference is smaller than a threshold the watershed is erased (Fig. 6d).
E. For the dark object detection, e.g. hemorrhages, the blood vessels will be extracted in form of many spots distributing along the vessels (Fig. 6f). Therefore, the results of some other successful blood vessel detection [6] is used to mask these spots to leave non-blood vessel dark objects, e.g. microaneurysms and hemorrhages (Fig. 6g).

Fig. 5. Histogram of color difference image—thresholding to suppress irrelevant objects (relevant objects correspond to dark pixel)

![Histogram of color difference image](image)

Fig. 6. Watershed transform of one image block. (a) Color difference image of bright objects; (b) Inner marker and outer marker for watershed transform; (c) Watershed results of (b); (d) Verification of watershed results by checking pixel value difference between inside and outside watershed; (e) Color difference image of dark objects; (f) Watershed results of (e); (g) Verification of watershed results by masking blood vessel and pixel value checking.

Although the optic disc and the macula can be annotated by the above watershed method together with post-understanding, it is not discussed in this paper. We simply use available techniques to locate the two normal objects [9][10]. Because there is no preset abnormality on optic disc the obtained bright objects in its region are erased. For the same reason, the obtained dark objects in macula region are erased too. Finally the abnormalities leave. The results of abnormality detection of a fundus image are shown in Fig. 7. One can see most of abnormalities belonging to the first class are extracted.

4. Conclusion

A watershed method for the abnormality detection in color fundus images is proposed in this paper, which is performed on the object-based color difference image. In the color difference image obtained from Luv color space, the bright object and dark object are highlighted respectively. With a pre-thresholding to suppress undesired background and
object and a post-verification to check the intensity difference between the object detected and its surrounding, the watershed transform is successfully utilized to extract the abnormalities without the over-segmentation problem.

![Image](image_url)

Fig. 7. Results of bright (a) and dark (b) abnormalities extraction

References:


