Human Visual Perception and Retinal Diseases

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ABSTRACT: Retinal diseases are causing alterations of the visual perception leading sometimes to blindness. For this reason, early detection and diagnosis of retinal pathologies is very important. Using digital image processing techniques, retinal images may be analyzed quickly and computer-assisted diagnosis systems may be developed in order to help the ophthalmologists to make a diagnosis. In this paper we described shortly two computer-assisted systems for the detection of retinal landmarks (optic disc and vasculature) together with a brief introduction to the human visual system and to some alterations of the visual perception caused by retinal diseases.

1 INTRODUCTION:

1.1 ***The Human Visual System:*** The human visual system has the ability to assimilate information from visible light which reaches the eye. Visual perception is the ability of the brain to interpret the information assimilated.

Light reaches the eye and forms an image on the retina. The retina is a thin layer of photoreceptors located at the back of the eye. (Figure 1)

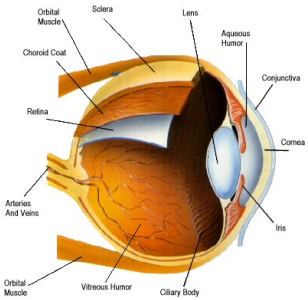


Fig. 1 Structure of the human eye (from http://library.thinkquest.org)

In the retina there are two types of photoreceptors: rods and cones. The cones are contained in the macula. The fovea is the part of the retina which contains the biggest number of cones. Cones function best in bright light and are responsible for color perception. The rods are distributed throughout the peripheral retina and function best in dim light. They are responsible for peripheral and night vision.

The macula is located roughly in the center of the retina, temporal to the optic nerve. It is a small part of the retina responsible for detailed central vision (such as reading). The fovea is the very center of the macula. The optic nerve is located near the macula and connects the retina to the visual cortex in the back of the eye, transmiting electrical impulses from the retina to the brain. When examining the back of the eye, a portion of the optic nerve called the optic disc can be seen. The optic disc is the point where the optic nerve enters the retina and it is not sensitive to light. Due to the absence of the retina's photoreceptors from the optic nerve, it is called also blind spot.

The blood vessels of the retina radiate from the center of the optic nerve as it can be seen from Figure 2.

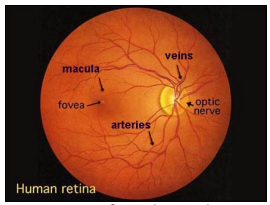


Fig. 2 Structure of the human retina (from http://www.eusem.com)

1.2 ***Retinal Diseases:*** Diseases of the retina can be responsible for partial or total loss of vision. Some retinal pathologies are caused also by the presence of other diseases such as diabetes. Retinal pathologies may be divided into three main groups (following the retinal component they affect): optic disc pathologies, macula pathologies and vasculature pathologies.

The symptoms presented by patients affected by retinal dis-

eases may be:

1. peripheral vision (ability to see objects located on the side of the field of vision) or side vision deteriorated (Figure 3(b)) - in the presence of glaucoma, a disease that causes injury to the eye's optic nerve.

2. reduced visual acuity (ability to see clear) (Figure 4). Blurring of vision may affect sight in the presence of diseases such as papilledema (optic disc swelling due to intra cranial pressure) or age-related macular degeneration AMD (is a disease associated with aging that slowly destroys central vision which is needed for seeing objects clearly).

3. poor color vision (ability to see colors) (Figure 5). Patients with optic atrophy (disease which affects the optic nerve by loosing part of optic disc nerve fibers) may have difficulties with color vision. Color vision is perceived mainly by the macula, which is the central vision portion of the retina. Thus any pathology affecting the macula may cause also difficulties with color vision.

4. obscured visual field (Figure 3(c)). Vision may be obstructed by spots of blood caused by swelled and leaky blood vessels of the retina like in the case of diabetic retinopathy.

5. image distortion (Figure 6). Straight lines may appear broken or distorted in the presence of macular pathologies, like for example AMD.

(a) Normal vision (b) Same scene viewed by a person with glaucoma (c) Same scene viewed by a person with diabetic retinopathy

Fig. 3 Peripheral vision lost - indication of glaucoma and obscured visual field - indication of diabetic retinopathy (from http://www.nei.nih.gov)

Fig. 4 Blurred scene viewed by a person with reduced visual acuity (from http://www.beamdaware.co.uk)

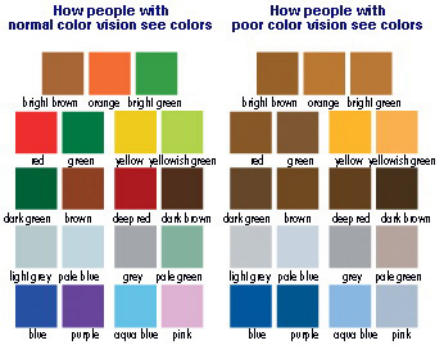


Fig. 5 Colors seen by people with normal color vision and people with poor color vision (from http://www.gracia-net.jp)

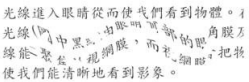
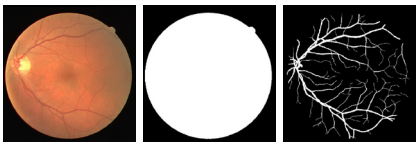


Fig. 6 Scene viewed by a patient with macular disease (from http://www.cuhk.edu.hk)

1.3 ***Retinal Image Analysis:*** Extraction of main landmark features in retinal images, such as the optic disc, the vessels and the macula, is fundamental in the automated diagnosis of retinal pathologies. The process of extraction of these landmarks is based on retinal digital image analysis techniques. The retinal digital images may be used for analyzing the retina non-invasively in vivo.

The public digital retinal images database used for experiments is DRIVE (Digital Retinal Images for Vessel Extraction) database. The photographs were obtained from a diabetic retinopathy screening program in The Netherlands. The screening population consisted of 400 diabetic subjects between 25 - 90 years of age. Forty photographs

have been randomly selected. Each image has been JPEG compressed. The images were acquired using a Canon CR5 non-mydriatic 3CCD camera with a 45 degree field of view (FOV). Each image was captured using 8 bits per color plane at 768 by 584 pixels. The FOV of each image is circular with a diameter of approximately 540 pixels. For this database, the images have been cropped around the FOV. For each image, a mask image is provided that delineates the FOV. Manual segmentations of the vasculature are available also. (Figure 7) All images are available for download from the web site of the Image Sciences Institute of the University Medical Center Utrecht (http://www.isi.uu.nl/Research/Databases/DRIVE/download.php).



(a) (b) (c)

Fig. 7 Example of DRIVE data: (a) retinal image; (b) mask image; (c) ground truth segmentation

2 AUTOMATED DETECTION OF RETINAL LANDMARKS

2.1 ***Optic Disc:*** Optic disc (OD) localization is, for example, the main step for developing automated screening systems for diabetic retinopathy. Many inflammatory pathologies cause obvious changes in the optic nerve, like the optic neuritis, Horton's arteritis or some rheumatic pathologies. For instance, in the optic neuritis, the optic nerve may appear swollen. The pathology for which a careful analysis of the optic disc is absolutely necessary is the glaucoma: chronic disease with progressive development that represents one of the main causes of blindness in the world.

The OD in a healthy retinal image usually appears as a bright yellowish and circular shape which is partly covered with vessels. Due to the luminance or the blurriness the optic disc may appear different from image to image. The OD-appearance may also be affected by diseases (may be covered by too many vessels or it may be bigger or smaller than normal). In some diseases, like for instance in the presence of optic disc drusen (bright regions on the OD), the OD is not anymore circular. The margins of the disc are in this case irregular and blurred.

The detection of the optic disc is important also because the OD is the origin of the vascular network and it can be used as a starting point for vessel tracking. Moreover, the OD may be used as a reference point for image registration.

In [1] we presented our approach for the automatic detection of the optic disc. The goal of our methodology was to provide automatically the contour of the OD. The first step was to localize roughly the position of the OD. After identifying the position of the OD, we estimated it's boundary by fitting the OD with a circle. In order to find the best circle which fits the OD we were not using the Hough transform because we didn't want to establish a priori a range for the radius of the circle or to establish a threshold value on the number of pixels of the circle. The best circle which fits the OD was chosen from a set of circles, by using the correlation coefficient of the regression line of the points of maximum derivatives in the y direction (these derivatives are computed after mapping the circle into the polar coordinates space). (Figure 8 and 9)

To compute the correlation coefficient of a set of n data points (x_i, y_i), we first consider the sum of squared values ss_{xx}, ss_{xy} and ss_{yy} about their respective means,

$$ss_{xx} = \sum_{i=1}^{n}(x_i - \overline{x})^2 = (\sum_{i=1}^{n} x_i^2) - n\overline{x}^2$$

$$ss_{yy} = \sum_{i=1}^{n}(y_i - \overline{y})^2 = (\sum_{i=1}^{n} y_i^2) - n\overline{y}^2$$

$$ss_{xy} = \sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y}) = (\sum_{i=1}^{n} x_i y_i) - n\overline{xy},$$

where $\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$ and $\overline{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$.

Then, the correlation coefficient is

$$r^2 = \frac{ss_{xy}^2}{ss_{xx}\, ss_{yy}}.$$

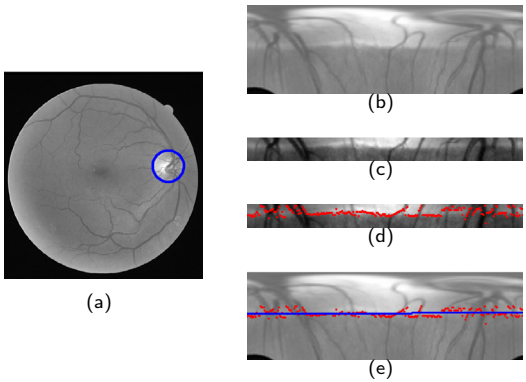


Fig. 8 The marked circle (a) and its mapping image (b); the strip of the mapping image (c) and the maximum derivatives in the y direction (d); the regression line that best fits the set of the derivatives for the circle that best fits the OD (e)

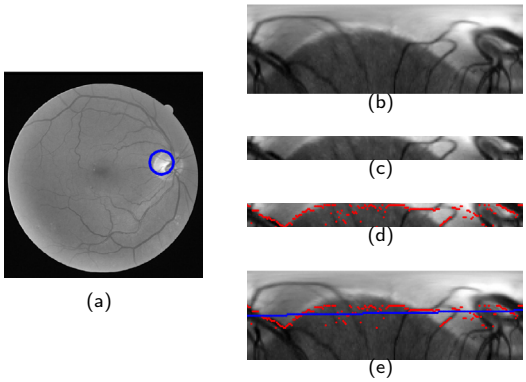


Fig. 9 The marked circle (a) and its mapping image (b); the strip of the mapping image (c) and the maximum derivatives in the y direction (d); the regression line that best fits the set of the derivatives for a circle that doesn't fit the OD (e)

The equation of the regression line that best fit the set of the points will be

$$y = a + bx,$$

where $a = \frac{s_{xx}s_y - s_{xy}s_x}{ns_{xx} - s_x^2}$, $b = \frac{ns_{xy} - s_x s_y}{ns_{xx} - s_x^2}$, $s_x = \sum_{i=1}^{n} x_i$ and $s_y = \sum_{i=1}^{n} y_i$.

We expect to have a correlation coefficient big (close to 1) for the circle that best fits the OD (as the maximum derivatives in the y direction are expected to be at the OD boundary and are expected to be best fitted by the line $y = \rho$, where ρ is the radius of the circle that best fits the OD).

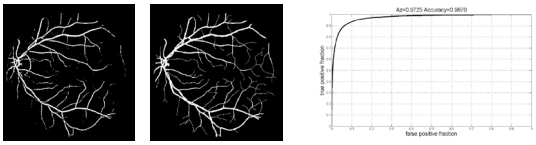
For example, for the image in Figure 8(a), the correlation coefficient for the circle that best fit the OD is 0.9947, meanwhile for example for a circle which doesn't fit the OD is 0.9787 (Figure 9(a)).

The circle that best fits the OD is chosen as the circle with the maximum correlation coefficient associated.

2.2 ***Retinal Vessels:*** The study of the retinal vasculature is very important because it is the only part of the blood circulation system that can be observed non-invasively and in this way a number of pathologies can be diagnosed by the detection of lesions in the retinal vasculature, e.g., diabetes, hypertension, arteriosclerosis. Automatically generated vessel maps have been used to guide the identification of retinal landmarks like the optic disc and the fovea. The vascular tree extracted from a retinal image is used also for image registration. Branching and crossover points in the vasculature structure are used as landmarks for image registration.

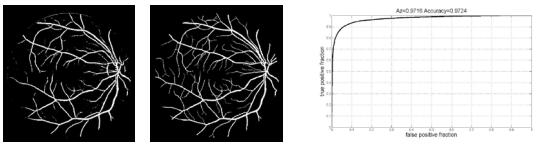
In [3] we introduced FABC (Feature-based AdaBoost Classifier), a supervised method which trains an AdaBoost classifier with manually labeled images. The feature vector used is a rich collection of measurements at different spatial scales, including the output of various filters (Gaussian and derivatives of Gaussian filters, matched filters, two-dimensional Gabor wavelet transform), and the likelihood of structures like edges and ridges via numerical estimation of the differential properties of the intensity surface (principal and mean curvatures, principal directions, root mean square gradient). This feature vector encoded a rich description of vessel-related image properties, namely local (pixel's intensity, Hessian-based measures), spatial (e.g., the gray-level profile of the cross-section of a vessel can be approximated

by a Gaussian curve) and structural (e.g., vessels are geometrical structures which can be seen as tubular). After the classifier is trained, it is applied to classify pixels as vessel or non-vessel in images not included in the training set.



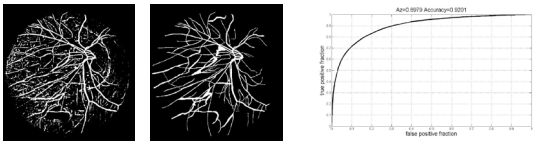
(a) Az=0.9725 ACC=0.9670 (b) ground truth segmentation (c) ROC curve associated

Fig. 10 Best result of FABC in terms of area under the ROC curve (image 21_*training.tif* from the DRIVE database)



(a) Az=0.9716 ACC=0.9724 (b) ground truth segmentation (c) ROC curve associated

Fig. 11 Best result of FABC in terms of accuracy (image 19_*test.tif* from the DRIVE database)



(a) Az=0.8979 ACC=0.9201 (b) ground truth segmentation (c) ROC curve associated

Fig. 12 Worst result of FABC in terms of both area under the ROC curve and accuracy (image 34_*training.tif* from the DRIVE database)

The performance of the binary classifier described above are measured using Receiver Operating Characteristic (ROC) curves. ROC curves are represented by plotting true positive fractions versus false positive fractions as the discriminating threshold of the AdaBoost algorithm is varied. The area under the ROC curve (Az) measures discrimination, that is the ability of the classifier to correctly distinguish between vessel and non-vessel pixels. An area of 1 indicates a perfect classification. We compute also the accuracy, that is an important quality parameter. The accuracy (ACC) is the fraction of pixels correctly classified.

CONCLUSION: We applied the algorithm for the automated detection of the OD on the 40 images from the DRIVE database and we achieve a 95% success rate for the localization of the OD which is a remarkable result with respect to past results. We achieved also a 70% success rate for the circle that best fits the OD.

Overall, the mean of the areas under the ROC curves generated by FABC over all DRIVE images was 0.9536 and the accuracy was 0.9575. To give a feeling of the quality of the segmentation, we show in Figure 10, 11 and 12 the best and the worst results produced by FABC on the DRIVE set in terms of area under the ROC curve and accuracy, along with ground truth segmentations and associated ROC curves.

A system, which allows a standardized study of the retinal landmarks is extremely useful. It provides an accurate and repeatable evaluation, independently from the operator's skill. The great advantage of using a such system, based upon the analysis of the digital fundus images, is that the system is completely safe and non invasive for the patient.

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[3] Lupaşcu, C.A., Tegolo, D. and Trucco, E.. *FABC: Retinal Vessel Segmentation using AdaBoost*. submitted to IEEE Transactions on Information Technology in BioMedicine.