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Severe: Segmenting vessels in retina images☆

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ABSTRACT

This paper presents the unsupervised retinal vessels segmentation method, SEVERE (SEgmenting VEssels in REtina images), which is based on the direction map of retina scan images assigning each pixel one out of twelve discrete directions. SEVERE works on the green channel of RGB retina scan images. It does not require any pre-processing phase and all the computations are done exclusively on the direction map. SEVERE has been checked on publicly available datasets producing qualitatively satisfactory results and outperforming other existing methods in terms of quantitative performance evaluation parameters, such as accuracy and sensitivity.

1. Introduction

Body characteristics, e.g., the face or the voice, have been qualitatively used by human beings to recognize each other since the dawn of human history, but it is only since little more than one century that some body measurements have become an effective part of person identification systems. The important discovery of the distinctiveness of the human fingerprints stimulated the use of biometrics for criminal investigations. Automatic fingerprint identification has been extensively used for the identification of criminals by automatically matching unknown fingerprints against a database of known prints. Successively, also other biological measurements have been considered and biometric systems have been employed in a variety of applications. Schematically, we could categorize the possible applications in the following five main groups: (i) forensic, e.g., identification of criminals, surveillance, (ii) government, e.g., identification cards, driver's licenses, voter ID and elections, benefits distribution and social services, employee authentication, (iii) commercial, e.g., account access, online banking, PC/Network access, e-commerce, time and attendance monitoring, (iv) health-care, e.g., access to personal information, patient identification, and (v) traveling and immigration, e.g., border crossing, passports.

In principle, any physiological or behavioral human characteristic could be employed in a biometric system, provided that it is characterized by universality, distinctiveness, permanence and collectability. In other words, a biometric characteristic should be typical of all human beings, should be sufficiently different for any two different human beings, should remain as much as possible stable for a long period of time, and should be quantitatively measurable. Moreover, also the vulnerability to spoofing of the body characteristics, their impact on accuracy and speed of the recognition process, and the invasiveness of the biometric acquisition devices should be taken into account when devising a biometric system for personal recognition.

Human retina is the body characteristic that we consider in this paper. The retina is a thin layer of cells, placed at the back of the eyeball, whose main task is to convert light into nervous signals. Some cooperation of the end user is necessary to perform the retina scan. The end user should remove glasses, place the eye close to the scanner, stare at a specific point and remain still for approximately 10–15 s. The acquisition of the retinal pattern is accomplished by casting an unperceived beam of low-energy infrared light into the eye. The beam of light traces a standardized path on the retina. The amount of reflection during retinal scan varies since retinal blood vessels absorb light more readily than the surrounding tissue.

The structure of the blood vessels of the retina is very complex. Every eye has its own totally unique pattern of blood vessels (even identical twins have distinct patterns). Although retinal patterns may be altered in case of diseases such as glaucoma, diabetes, and autoimmune deficiency syndrome, the retina remains typically stable over a person's lifetime. The performance of retina based biometric systems is considered as the best in term of accuracy. Moreover, human retina has not yet been forged and the retina of dead persons decays too rapidly to be used to deceive a retinal scan. Thus, except for the fact that retina scan is often thought to be inconvenient and intrusive so that it is difficult to gain general acceptance by the end users, the retina is one of the body parts that satisfies perfectly all the desirable issues for a biometric system [1,2].

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Accordingly, retina biometrics systems are of interest, especially when maximum security is necessary, e.g., for military applications and for environments, such as Government and banking.

Manual segmentation of retinal blood vessels requires training and skill. Moreover, it is a long and tedious task. Thus, automatic retinal vessel segmentation is highly desirable and a number of supervised and unsupervised methodologies are available in the literature. Supervised methodologies use classifiers that are trained to distinguish between vessel and non-vessel pixels. Unsupervised methods do not employ classifiers and are based on the use of thresholding or other specific rule-based techniques to segment the image. In [3–7], retinal vessels were enhanced by means of matched filters, and segmentation was successively achieved by means of adaptive thresholding. In [8–11], blood vessel segmentation has been achieved by means of mathematical morphology. In [12–15], starting from a group of suitably selected seed points, vessels were tracked following their centerlines. Other unsupervised methods can be found in [16–19]. In [20–28], supervised segmentation methods were suggested, where k-Nearest Neighbor, Bayesian classifier in combination with multi-scale analysis of Gabor wavelets, combination of support vector machine with a linear kernel, and ensemble of boosted and bagged decision trees were used.

This paper presents the unsupervised retinal vessels segmentation approach SEVERE (SEgmenting VEssels in REtina images) based on the direction map constructed starting from the retina scan image. SEVERE is the follow up of a recently suggested method, [19], which is based on the use of the watershed transform and on the combination of directional and contrast information. With respect to the method in [19], SEVERE is computationally more advantageous, since it does not require the computation of the watershed transform; moreover, SEVERE does not include any pre-processing phase and all the computations are done exclusively on the direction map; finally, the performance of SEVERE is noticeably better.

The rest of the paper is organized as follows. In Section 2 some basic notions and the description of the segmentation method SEVERE are given; in Section 3 the experimental part of the work is illustrated; finally, in Section 4 a brief conclusion is given.

2. The segmentation method SEVERE

We work with retina images in the RGB color space. As generally done by the scientific community active in retinal vessels segmentation, we use only the green channel G. In fact, as it can be seen with reference to Fig. 1, G is the image with the highest contrast between vessels and background; in turn, the red channel R is the image with the lowest contrast, and the blue channel B is characterized by a very small dynamic range. The image G in Fig. 1 bottom right will be used in the following as running example. The gray-levels of pixels of G are in the range [0, 255], where higher values correspond to lighter pixels. Thus, gray-levels 0 and 255 respectively correspond to black and white. The images used in this paper are taken from the publicly available database Digital Retinal Images for Vessels Extraction DRIVE [23].

SEVERE requires six steps, respectively accomplishing the following processes: (i) construction of the direction map DM and preliminary segmentation, (ii) editing of DM to correct some directions erroneously computed, (iii) removal of small noisy foreground components, (iv) removal of noisy background components, (v) removal of noisy foreground parts in correspondence with the boundary of the mask, and (vi) removal of noisy peripheral foreground parts.

2.1. Direction map construction

Pixels belonging to vessels are generally darker than pixels in the background and are grouped along lines with different directions.

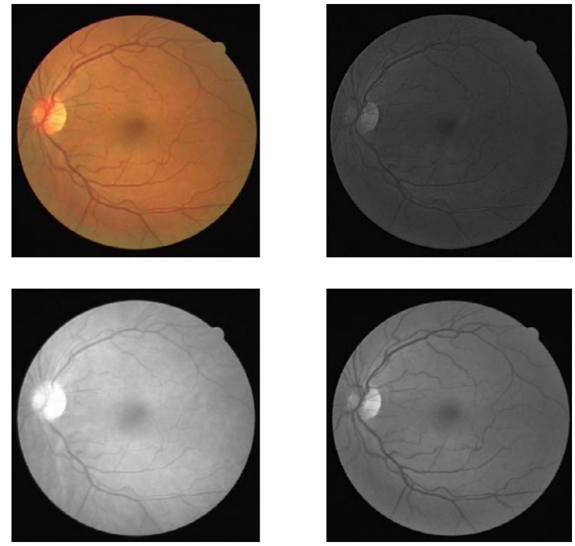

Fig. 1. From top left to bottom right: retinal image (image 01_test of DRIVE database, [23]), and its blue, red and green channels. (For interpretation of the references to colour in this figures legend, the reader is referred to the web version of this article)

Thus vessel pixels can be detected by building a direction map, where each pixel in the image is assigned a direction.

To build the direction map, we use a discrete $n \times n$ directional mask. Thus, $2 \times n - 2$ different directions are possible, passing through the central pixel p and linking it to each pair of opposite pixels out of the $2 \times n - 2$ pixels delimiting the mask. Of course, along each of the obtained straight lines it is possible to go in two opposite directions (say positive and negative directions, with respect to a Cartesian coordinate system centered on p).

Our choice is to use $n = 7$, so that 12 directions d_i, $i = 1,2, \dots , 12$, are possible and the angle between any direction d_i and the successive direction d_{i+1} is 15 °. The 12 directional templates, T_d_i, corresponding to the 12 directions d_i, $i = 1,2, \dots , 12$, are shown in Fig. 2, where different colors are used for different directions. For each template, only the pixels along the proper direction are set to 1, all other pixels are set to 0.

The selection of the proper size for the directional mask has been done by taking into account the thickness of the vessels and the smallest distance in between them. For the images in the DRIVE database the former ranges from 1 to 10 pixels, while the latter is about four pixels. In fact, if the mask is too little sized, when it is centered on the innermost pixels of a vessel (or is placed halfway in between two vessels) very small variations in gray-level occur along each of the different directions, which would make all directions to be equally possible and will then prevent the selection of the proper directions for those pixels. If the mask is too large, it may include

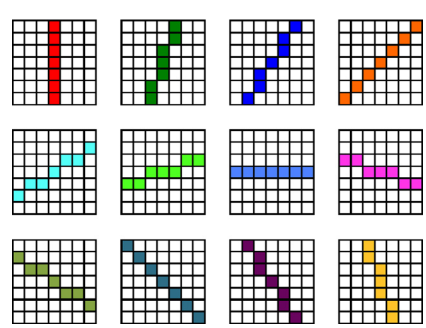

Fig. 2. From top left to bottom right: the 12 directional templates T_d_i for the 12 different directions d_i ($i = 1,2, \dots , 12$) possible in a 7×7 directional mask.