SOFT COMPUTING BASED TECHNIQUE FOR OPTIC DISC AND CUP DETECTION IN DIGITAL FUNDUS IMAGES

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Introduction

INTRODUCTION

Glaucoma, the second leading cause of blindness worldwide, is a group of chronic diseases that gradually damages the eye's optic nerve.

This disease is divided in two major subtypes:

- open-angle: caused by an increasingness in the eye pressure due to trabecular blockage.
- angle-closure: caused by a permanent obstruction of the aqueous humor outflow from the eye.

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Diagnosis: three different sets of examinations

- evaluation of the intraocular pressure, (drawbacks and expensive treatment)
- evaluation of the visual field, (drawbacks and expensive treatment)
- evaluation of the optic nerve head damage.

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As the disease advances, the disc area is progressively occupied by the cup.

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Novel approach for this task based on Soft Computing techniques.

Soft Computing techniques are able to handle the imprecision and uncertainty present in the images more efficiently than other classical paradigms.

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Steps:

1. optic vessels segmentation and removal,
2. inpainting and optic disc and cup detection.

Fuzzy Mathematical Morphology

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This theory relies on the use of fuzzy morphological operators defined using fuzzy conjunctions and fuzzy implication functions.

Definition

An increasing binary operator $C : [0,1]^2 \to [0,1]$ is a *fuzzy conjunction* whenever it is increasing in both variables and it satisfies $C(0,1) = C(1,0) = 0$ and $C(1,1) = 1$.

Definition

A binary operator $I : [0,1]^2 \to [0,1]$ is a *fuzzy implication function* if it is decreasing in the first variable, increasing in the second one and it holds that $I(0,0) = I(1,1) = 1$ and $I(1,0) = 0$.

Definition

Let C be a fuzzy conjunction and I be a fuzzy implication function. The fuzzy dilation $\mathcal{D}_C(A, B)$ and the fuzzy erosion $\mathcal{E}_I(A, B)$ of a grey-scale image A and a grey-scale structuring element B are defined as:

$$\mathcal{D}_C(A, B)(y) = \sup_{x \in d_A \cap T_y(d_B)} C(B(x-y), A(x)),$$

$$\mathcal{E}_I(A, B)(y) = \inf_{x \in d_A \cap T_y(d_B)} I(B(x-y), A(x)),$$

where d_A and d_B denote the definition domains of A and B and $T_y(d_B)$ is the translation of the fuzzy set d_B by vector $y \in \mathbb{R}^2$ given by $T_y(d_B)(z) = d_B(z-y)$.

FUZZY MATHEMATICAL MORPHOLOGY

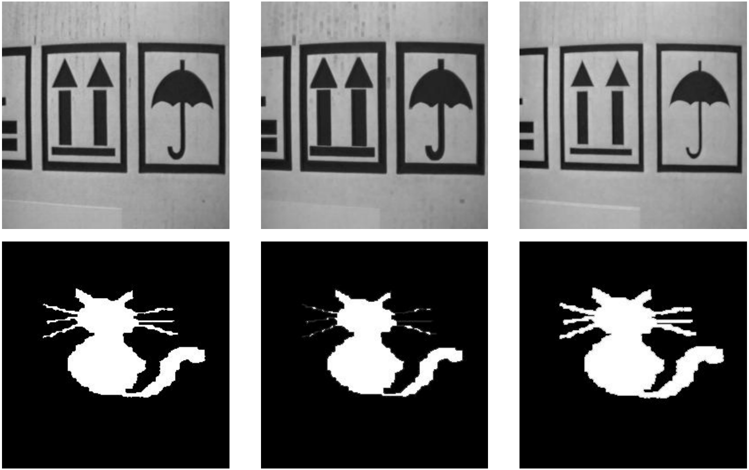

Figure: From left to right, original image, fuzzy erosion and fuzzy dilation.

From these two basic operations and the reflected structuring element, $\bar{B}(x) = B(-x)$, we can construct the closing $\mathcal{C}$ and the top-hat transformation by closing $\mathcal{THC}$:

$$\mathcal{C}_{C,I}(A, B) = \mathcal{E}_I(\mathcal{D}_C(A, B), \bar{B}), \quad \mathcal{THC}_{C,I}(A, B) = \mathcal{C}_{C,I}(A, B) - A.$$

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- Fuzzy dilation: expands the foreground object,
- fuzzy erosion: diminishes it.

- Closing operator: enlarges the foreground object by filling sharp or thin areas of the background,
- top-hat transformation by closing: enhances dark regions removed by the closing.

For the vessel segmentation problem, we will use as fuzzy conjunction the nilpotent minimum t-norm, along with its residual implication, the Fodor implication:

$$T_{\mathrm{nM}}(x,y) = \begin{cases} 0, & \text{if } x+y \leq 1, \\ \min\{x,y\}, & \text{otherwise,} \end{cases}$$

$$I_{\mathrm{FD}}(x,y) = \begin{cases} 1, & \text{if } x \leq y, \\ \max\{1-x,y\}, & \text{otherwise.} \end{cases}$$

Definition

Let C be a conjunction, let I be a fuzzy implication, let A be a multivariate image and let B be a structuring element. Then, the *soft color dilation* of A by B, $\mathcal{D}_C(A, B)$, is

$$\mathcal{D}_C(A, B)(y) = \Big(C\big(B(x-y), A_1(x)\big),\ A_2(x),\ \ldots,\ A_m(x)\Big),$$

s.t. $x \in d_A \cap T_y(d_B)$ and $C\big(B(x-y), A_1(x)\big)$ is maximum, and the *soft color erosion* of A by B, $\mathcal{E}_I(A, B)$, is

$$\mathcal{E}_I(A, B)(y) = \Big(I\big(B(x-y), A_1(x)\big),\ A_2(x),\ \ldots,\ A_m(x)\Big),$$

s.t. $x \in d_A \cap T_y(d_B)$ and $I\big(B(x-y), A_1(x)\big)$ is minimum.

Definition

Let A be a multivariate image and let B be a structuring element. Let C be a conjunction and let I be a fuzzy implication function. Then, the *closing* of A by B, $\mathcal{C}_{C,I}(A,B)$, and the *opening* of A by B, $\mathcal{O}_{C,I}(A,B)$, are defined as:

$$\mathcal{C}_{C,I}(A,B) = \mathcal{E}_I(\mathcal{D}_C(A,B),\bar{B}), \quad \mathcal{O}_{C,I}(A,B) = \mathcal{D}_C(\mathcal{E}_I(A,B),\bar{B}).$$

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P. Bibiloni, M. Gonzalez-Hidalgo and S. Massanet, Soft color morphology, *2017 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, Naples, 2017, pp. 1-6. doi: `10.1109/FUZZ-IEEE.2017.8015388`

These operators preserve colors in any color space if the structuring element is a binary image.

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When dealing with fundus images, these operators are performed using the CIELab space.:

L*: lightness,

a* and b*: chromatic information of a pixel.

For L*a*b*-encoded images, these mathematical morphology operators generalise those of the fuzzy mathematical morphology and they preserve the chromatic components.

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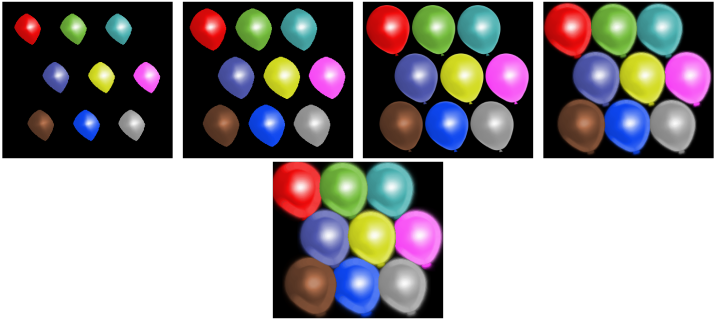
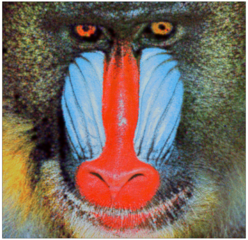
Inpainting problem: Minimum operator as conjunction $T_M(x, y) = \min\{x, y\}$; and its residual implication, the Gödel implication

$$I_{GD}(x, y) = \begin{cases} 1 & \text{if } x \leq y, \\ y & \text{if } x > y. \end{cases}$$

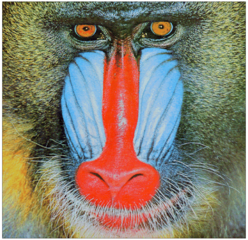
SOFT COLOR MORPHOLOGY



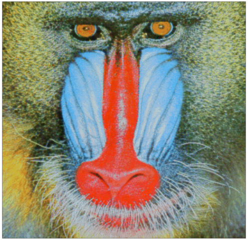
From left to right, erosion (left), the L*a*b*-encoded *Balloons* image (center) and dilation (right), using a 15 × 15-pixel (toward the center) or a 31 × 31-pixel (at the sides) Gaussian-shaped structuring element. The irregular shapes of the eroded balloons reflect their irregular illumination.



(a) Opening



(b) Original image

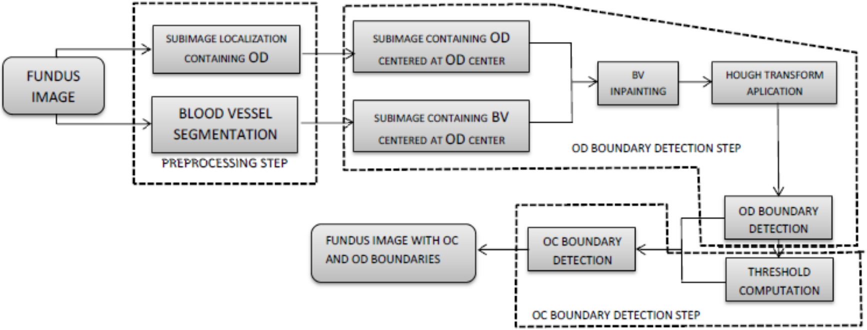


(c) Closing

Opening and closing of the L*a*b*-encoded *Mandril* image, using a 15×15-pixel Gaussian-shaped structuring element.

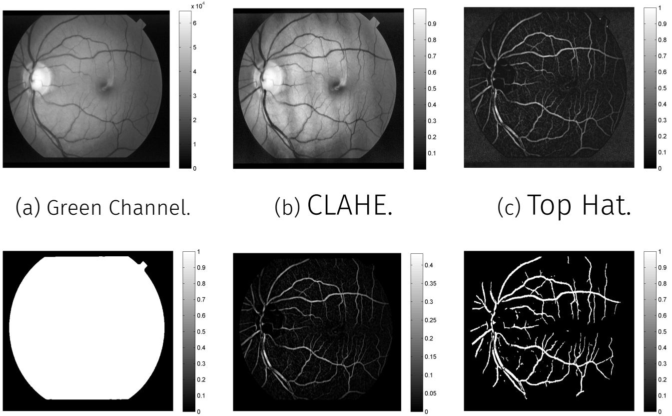
Algorithm for the optic and cup disc detection

ALGORITHM FOR THE OPTIC AND CUP DISC DETECTION



Flow chart of the optic disc and cup segmentation algorithm.

FIRST STEP: VESSEL SEGMENTATION AND OD CENTER LOCALISATION



(a) Green Channel. (b) CLAHE. (c) Top Hat.

(d) Background Mask. (e) Border Removal. (f) Hysteresis.

Figure: Intermediate steps of our segmentation method when processing the sample 235th from the STARE dataset.

FIRST STEP: VESSEL SEGMENTATION AND OD CENTER LOCALISATION

OD center localisation:

For the OD center localisation, the OD search space is reduced based on an OD probability map (determined by the projections of the L_1-norm image gradient and image intensity to the horizontal and vertical directions). Next, its brightest pixel is set as the candidate for OD center.

SECOND STEP: OD BOUNDARY DETECTION

OD boundary detection:

Two subimages of size $M \times M$ centered at OD center obtained in the first step are extracted: S from the original image, and V from the vessel segmentation image. $M = 200$.

V is used as mask image: pixels located as vessel in V subimage are marked as missing in the S subimage for a inpainting algorithm using soft color morhplogy.

Inpainting step: removes the vessels from the image making easier the OD and CD segmentations. Result: subimage IS.

SECOND STEP: INPAINTING ALGORITHM

Inpainting algorithm:

A iterative sequence of images is defined from the obtained image of the previous step.
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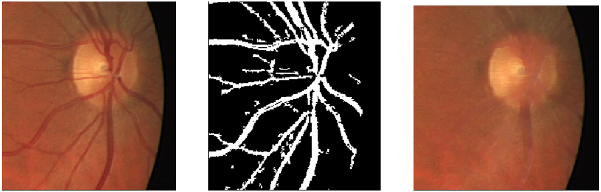

From left to right: S subimage, V subimage, and inpainted image.

SECOND STEP: OD BOUNDARY DETECTION

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From the subimage *IS*, we obtain its Luminance image *LIS*. We apply the Hough Transform (HT) to it. After that, the candidate circle with the highest metric is selected as the OD boundary.

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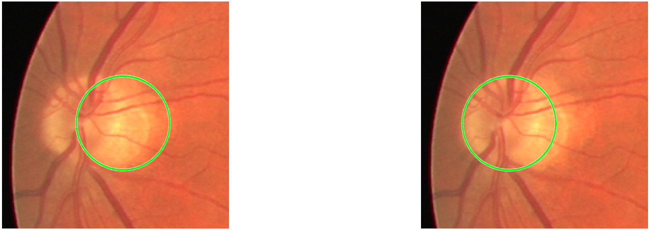

Results of the OD boundary detection step after inpaintig (right) and directly on the original fundus image (left).

Detection of the CD boundary

Let R_{LIS} be the region enclosed by the OD boundary in the luminance image LIS. We apply a thresholding to R_{LIS} with the threshold value given by $th = 1.2 \cdot mean(R_{LIS})$. Then, we fit a circle to the largest connected component (cc) of the obtained binary image, centred on its centroid and radius $r \approx \sqrt{area\,(cc)/\pi}$.

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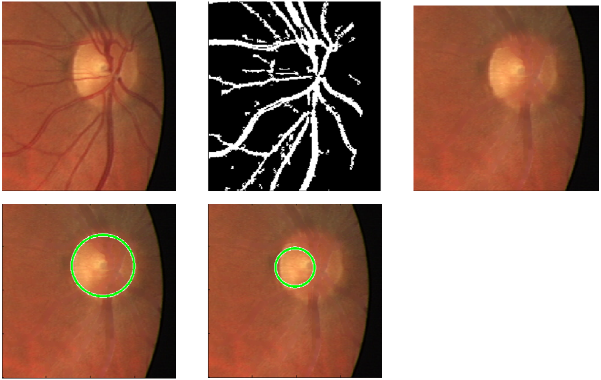
Output of the algorithm: display of the original fundus image with the CD and OD boundaries.

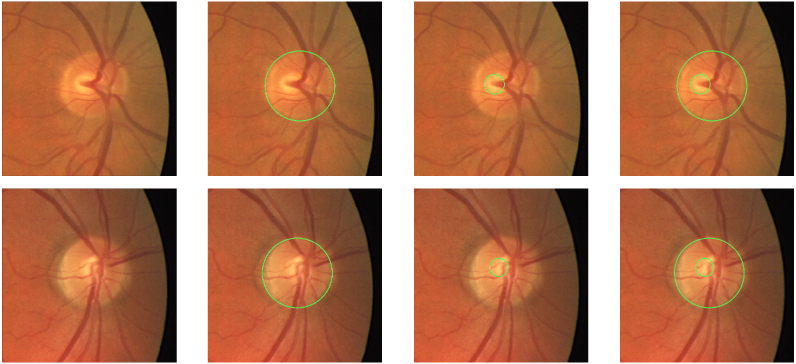
ALGORITHM FOR THE OPTIC AND CUP DISC DETECTION



Intermediate images obtained by the algorithm applied on the 19th image of the DRIVE database. From left to right and from top to bottom: sub-image centered at the OD center, vessel mask image, inpainted image, optic disc boundary and optic cup boundary.

Results

RESULTS



Original image and results obtained using the proposed algorithm for two different images. From left to right: sub-image centered at the OD center, OD boundary, CD boundary and both boundaries.

Conclusions and future work

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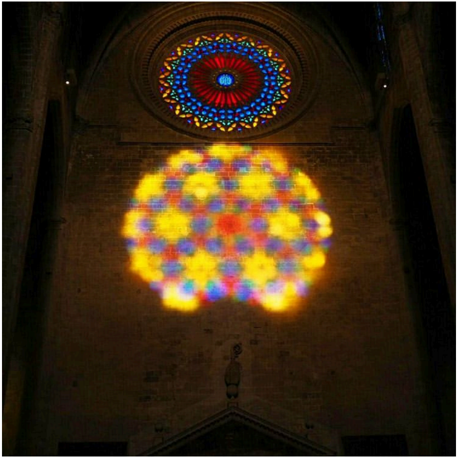
The preliminary results are very promising showing a visual accurate segmentation of both structures in the DRIVE database.

FUTURE WORK

Future work: compare our algorithm with other state-of-the-art algorithms based on different techniques from the qualitative and quantitative points of view.



Thanks for your attention!