Retinal Blood Vessel Segmentation by a MAS Approach

Carla Pereira[1], Jason Mahdjoub[2], Zahia Guessoum[2], Luis Gonçalves[3] and Manuel Ferreira[1]
[1]*Algoritmi Center, University of Minho, Campus de Azurém, 4800-058, Guimarães, Portugal*
[2]*CReSTIC – MODECO, University of Reims, Rue des Crayères, 51100, Reims, France*
[3]*Ophthalmology Service, Centro Hospitalar do Alto Ave, Guimarães, SA., 4835-044, Guimarães, Portugal*

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Abstract: Retinal blood vessels segmentation by color fundus images analysis has got huge importance for the diabetic retinopathy early diagnosis. Several interesting computational approaches have been done in this field, but none of them has shown the required performance due to the use of global approaches. Therefore, a new approach is proposed based on an organization of agents enabling vessels detection. This multi-agent approach is preceded by a preprocessing phase in which the fundamental filter is a Kirsch derivative improved version. This first phase allows an environment construction where the agents are situated and interact. Then, blood vessels segmentation emerges from agents' interaction. According to this study, competitive results were achieved comparing to those found in the present literature. It seems to be that a very efficient system for the diabetic retinopathy diagnosis can be built using MAS mechanisms.

1 INTRODUCTION

Diabetic retinopathy (DR) has been presented as the most common cause of blindness among working age people. Retinal blood vessels segmentation has got huge importance for the DR early diagnosis. Numerous research efforts have been done in segmenting blood vessels using image processing techniques applied to fundus images. Some of the approaches include matched filtering (Zhang et al., 2010); machine-learning methods (Staal et al., 2004), morphological operators (Mendonça and Campilho, 2006). The main difficulties in vessels accurate segmentation are pathologies presence, noise, the low contrast between vasculature and background, vessels width, brightness and shape variability. To solve the variability problem, it is important to adapt image interpretations, in loco, instead of only applying one algorithm on the entire image. A multi-agent system (MAS) is thus proposed as a solution since agents allow several algorithms cohabitation.

There are some studies reported in literature that associate MAS to image processing in medical images (Bovenkamp et al., 2004; Mahdjoub et al., 2006; Richard et al., 2004). This association has been revealed as a research expanded area. As far as known, multi-agent approaches have never been applied to retinal images. In this study, an approach based on Mahdjoub et al. (2006) previous study is applied to fundus images for the blood vessels segmentation. This new approach uses some image processing algorithms as concrete perception and action tools to define autonomous agents which interact among themselves and with environment (image). Then blood vessel segmentation emerges as a global behavior.

2 METHODOLOGY

The proposed approach uses a MAS model to improve retinal blood vessels edges detection resulting from a preprocessing phase. This preprocessing phase consists of a conventional image processing algorithms group providing information (environment) for the MAS model.

2.1 Image Pre-processing

In this first step, we first use the preprocessing phase from Niemeijer et al. (2005) developed study. In order to remove noise from fundus image while preserving the edges, Kuwahara filter (Kuwahara et al., 1976) was then applied. Finally, a modified Kirsch filter was employed to the image resulting

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from the last step. The Kirsch filtering is an image edges enhancing method using a basic convolution filter eight times rotated. The improved Kirsch filter (Mahdjoub et al., 2006) enables edges detection with a two pixels thickness whose external edge is represented by a positive or negative value, whereas the internal edge has an opposite value (Fig. 1 a). This enables the MAS model detection process since the blood vessels gradient reveals a specific pattern (Fig. 1 b), as they can be represented by two parallel linear segments series. Thus, the agents search for blood vessels edges by looking for this gradient specific pattern.

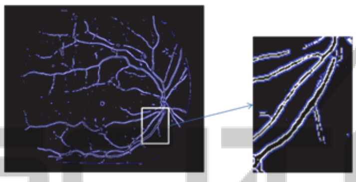

Figure 1: a) Modified Kirsch filter resultant image where the blue and white pixels represent negative and positive gradient values, respectively. b) One section image expanded version of a).

2.2 Multi-Agent System Model

MAS is composed by an agent set and their environment. The environment contains the green plane image in which each pixel contains the intensity grey level and a Boolean value defining if the pixel has already been explored by an agent. Moreover, when located in the environment the agents perceive the modified Kirsch gradient which defines a right visible edge. Agents are of several kinds with different behaviors according to their current state and perception: search agents (SA), following agents (FA), node agents (NA), and region agents (RA).

MAS is initialized with a SA launched on one of the white points from Fig. 1 a), randomly chosen. This SA in the "operating" state has to find edges belonging to blood vessel regions. It evolves in the environment by following positive gradient points. When it finds an edge, it initializes a new contour and launches two NAs belonging to this contour: one in the "active" state and another in the "inactive" one (Fig. 2 a). Furthermore, the SA changes its state to "suspended". Then the "active" NA has to allow contour extension and closure. Therefore, it determines the possible directions to follow the contour, creates FA and becomes "inactive" (Fig. 2 b). FA follows the detected edge until there is no direction to follow or until the contour reaches a specific length (Fig. 2 c). FA launches then an "inactive" NA on its position and an "active" NA on the perpendicular direction where it was moving (Fig. 2 d). Moreover, FA gives to the "active" NA information about this direction allowing it to launch another FA on the opposite direction (Fig. 2 e). When this FA reaches the initially launched "inactive" NA (Fig. 2 f) it launches a RA (Fig. 2 g) which will be responsible for the contour delimited region. RA sends a message to SA to change its state to "operating" and repeats all the process until all the blood vessels contours are founded by MAS. There so, MAS detects one contour each time avoiding regions intersection at this phase. Afterwards SA sends a message to all RAs to change their state to "filling". RA fills all the contours taking into account the image grey levels (Fig. 3). Finally, RAs attempt fusions with each other.

At the end of the process MAS has to reconstruct the vessels by representing them with a succession of regions initially represented by contours.

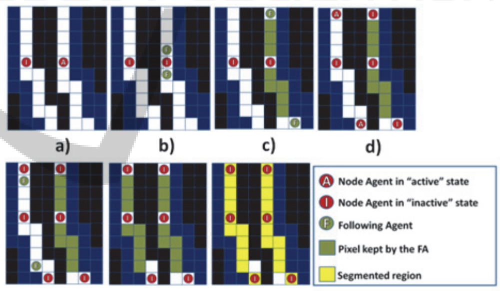

Figure 2: Contour formation graphical representation to which a RA is assigned.

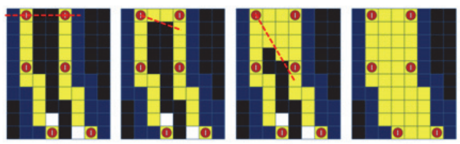

Figure 3: RA "filling" state graphical representation. It analyses the pixels located between each pair of two points belonging to its contour by determining the line linking these two points a) – c); d) all the points that are inside the contour, with grey level value similar to the contour average grey level value, are added to the region.

3 RESULTS AND DISCUSSION

The proposed MAS model was implemented with MadKit (Gutknecht and Ferber, 2000) and tested with the publicly available DRIVE dataset (Staal et al. 2004).

To measure the overall approach performance, it is important to compare the resulting image with the information detected by the Kirsch filter. Moreover, the differences between the binary resultant image with blood vessel segmentation and the ground truth vessel map should be evaluated. In that way, three common measurements, namely, sensitivity, specificity and predictive value (Lalkhen and McCluskey, 2008) were used for testing the proposed algorithm. Fig. 4 and Fig. 5 show the quantitative results obtained with this approach in the DRIVE dataset. The proposed approach results applied to normal retinal images are shown in Fig. 6. These illustrate the original and resulting images where the proposed approach had the best and the worst performance respectively, with 73.6% and 51.9% sensitivity values and 97.4% and 99.7% specificity values.

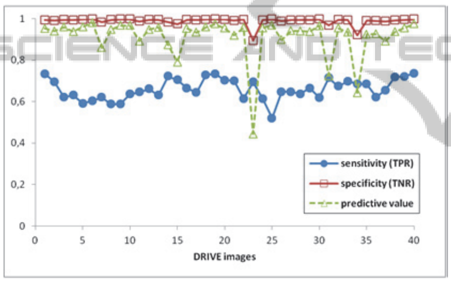

Figure 4: Sensitivity, specificity and predictive values obtained for the 40 images of the DRIVE database with the proposed approach.

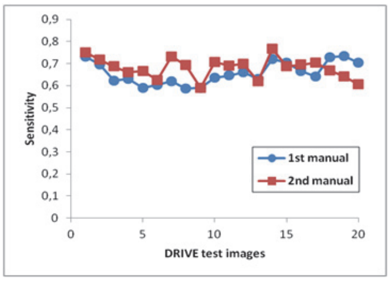

Figure 5: Sensitivity values obtained for the 20 images of the DRIVE database test set, using both hand labeled databases.

Fig. 7 illustrates a superimposed image of the hand labeled image with the hand labeled image after morphological opening and with MAS result.

In this figure, the white pixels represent the pixels common to the three images; the yellow and green pixels represent the pixels that belong to blood vessels but are not detected by MAS, that is, the

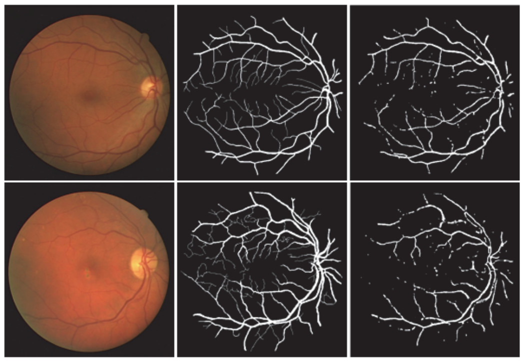

Figure 6: Images resulting where the proposed approach had the best (above) and worst (below) performance in the DRIVE database. From left to right: original color fundus image; hand labeled image; blood vessel segmentation using MAS approach.

false negative pixels; and the false positive pixels are represented in blue. As it can be seen, the most part of false positive pixels are located at the manually segmented vessels border and therefore, they should not be considered as false positive. Actually, manual blood vessels segmentation from retinal images is a very arduous and difficult task, leading two people to segment the same image in different ways. This can be observed in Fig. 5 where two different hand labeled images for the same color fundus images resulted in different sensitivity values with the same approach.

Analyzing Fig. 6 (right) and Fig. 7 it can be observed that MAS reconstructed the most part of the vessels, especially the thickest ones. Some of the thinnest vessels were also segmented but not all, affecting the sensitivity values. In fact, after removing the thinnest vessels from the hand labeled image (green pixels of Fig. 7) the sensitivity values of the proposed approach increased to values higher than 80%. So, improvements have to be made in MAS model to deal with the small vessels.

Moreover, there are some thickest vessels portions not detected by MAS model mostly near the FOV border and the optic disc contour. This last problem may be related with the preprocessing phase, mainly with Kuwahara filter since this often produces clearly noticeable artifacts. (Papari, et al., 2007).

Therefore, MAS is efficient in segmenting the blood vessels from where the edges were already detected in the preprocessing phase and in excluding the detected pixels that did not belong to vessels. Furthermore, MAS is able to close and aggregate regions that were delimited by interrupted edges in the kirsch resultant image, as a RA fusion process result.

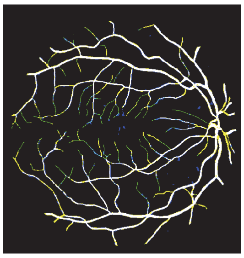

Figure 7: Hand labeled image superimposition with the hand labeled image after the morphological opening and with MAS result.

4 CONCLUSIONS

In this study, a MAS approach is proposed where agents enrich a traditional edge detector algorithm. The experiments show that the use of a MAS model in the micro level could be an effective way to segment structures in complex images such as retinal images. In fact, through environment perception and local interactions, a simple agent organization can have as global behavior the most part of retinal vasculature detection. The use of an improved version of agent society with some knowledge a priori about the retina proprieties, complemented with some other traditional image processing algorithms, could have the potential to develop a system to detect and differentiate all the anatomic and pathological structures of the fundus images. Such an approach will overcome the classic image processing algorithms that are limited to macro results which cannot take into account the local characteristics of a complex image. Therefore, it could be a fundamental tool responsible for a very efficient system development to be used in screening programs concerning DR diagnosis.

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