Detection of microaneurysms using ant colony algorithm in the early diagnosis of diabetic retinopathy

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ABSTRACT

Microaneurysms are lesions in the shape of small circular dilations which result from thinning in peripheral retinal blood vessels due to diabetes and increasing intra-retinal blood pressure. Because it is considered as the most important clinical finding in the diagnosis of diabetic retinopathy, accurate detection of these lesions bear utmost importance in the early diagnosis of diabetic retinopathy. The present study aims to accurately, effectively and automatically detect microaneurysms which are difficult to detect in color fundus images in early stage. To this aim, ant colony algorithm, which is an important optimization method, was used instead of conventional image processing techniques. First, retinal vascular structure was extracted from color fundus images in Messidor and DiaretDB1 data sets. Afterwards, the segmentation of microaneurysms was effectively carried out using ant colony algorithm. The same procedure was also applied to five different image processing and clustering algorithms (watershed, random walker, k-means, maximum entropy and region growing) in order to compare the performance of the proposed method with other methods. Microaneurysm images manually detected by a specialist eye doctor were used to measure the performances of above-mentioned methods. The similarities among microaneurysms which were automatically and manually segmented were tested using Dice and Jaccard similarity index values. Dice index values obtained from the study vary between 0.52 and 0.98 in maximum entropy, 0.55 and 0.88 in watershed, 0.75 and 0.86 in region growing, 0.55 and 0.78 in k-means, and 0.66 and 0.83 in random walker, and 0.81 and 0.9 in ant colony. Similar performance values were also obtained in Jaccard index. The results show that different performances were observed in the conventional segmentation of microaneurysms depending on the image quality. On the other hand, the ant colony based method proposed in this paper displays a more stabilized and higher performance irrespective of image contrast. Therefore, it is evident that the proposed method successfully detects microaneurysms even in low quality images, thus helping specialists diagnose them in an easier way.

Introduction

Motivation

Diabetic retinopathy (DR) is a microvascular complication arising out of diabetes mellitus, and is accepted as the main cause of blindness around the world [14]. Early diagnosis and appropriate treatment play a vital role in halting the progression of the disease and preventing blindness. Therefore, annual retina examination of diabetic patients must be performed by a specialist eye doctor based on color fundus images. Changes in anatomic structures such as eye retina, optical disk, macula and vessels as well as the existence of lesions such as microaneurysms and exudate help specialists in the detection of diseases. Microaneurysms are observed in the early stages of DR, and its

detection occupies an important position in the diagnosis of the disease. The density of microaneurysms in a retina is considered as an important criterion for the degree of DR and progression of the disease [15]. In this respect, computer based decision support systems which can enable specialists to diagnose and measure the degree of DR have been developed. These systems aim to automatically, reliably and rapidly detect lesions observed in DR such as exudate and microaneurysm. In the present study, an automatic microaneurysm segmentation based decision support system is designed for the early diagnosis of DR.

Background

Microaneurysms occur when retinal blood vessels cannot be fed due to diabetes. In other words, vessels become thinner when they are not

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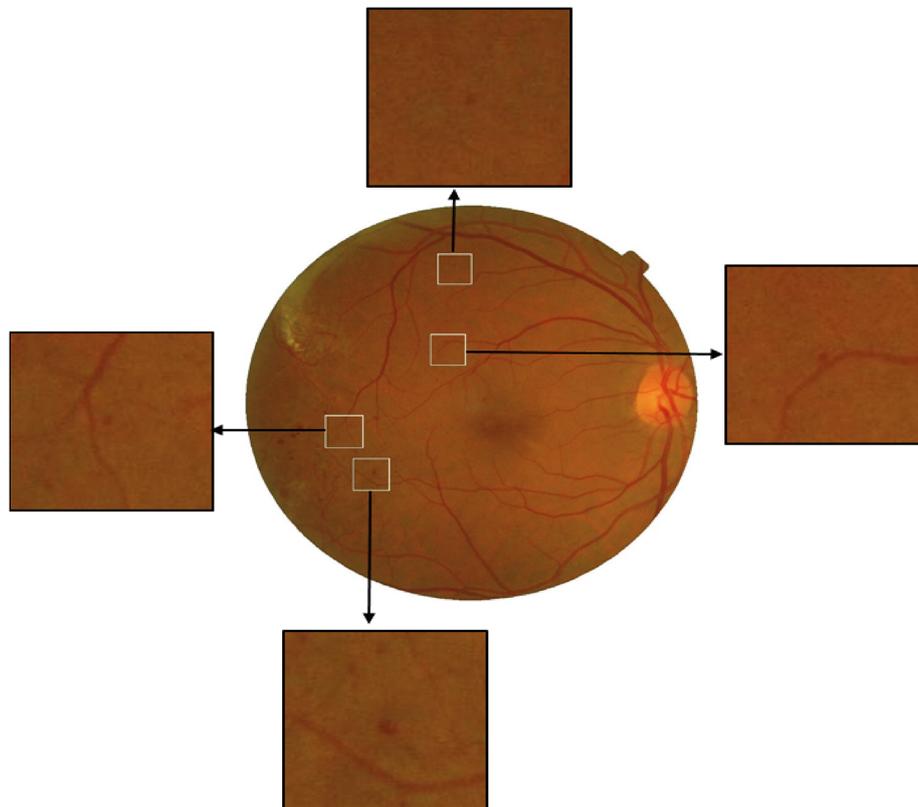 *E-mail address:* aalkan@ksu.edu.tr (A. ALKAN).

Fig. 1. Sample fundus image with a microaneurysm.

fed, and the related retinal regions dilates as a result of intravascular blood pressure. These regions usually appear as small red and circular in shape [6]. Existing microaneurysms are enlarged in color fundus image as shown in Fig. 1.

Technological developments in the field of biomedical image processing paved the way for designing image processing based automatic decision support systems that can be used for automatic detection of DR. Thanks to these support decision systems, specialists' work load remarkably decrease, and they can easily diagnose DR in an early stage. Several studies have been so far conducted in the literature which color fundus images were used to automatically analyze structures or lesions on the retina. Kamel et al. detected microaneurysms using an artificial neural network with learning vector quantization [19], which increases the accuracy of microaneurysm diagnosis but needs a long duration. Spencer et al. proposed a binary morphological and thresholding technique in the diagnosis of microaneurysm [28]. However, the existence of retinal vessels and changes in background color often decreases the performance of this technique. Another study by Spencer et al. proposed the detection of candidate regions using region growing algorithm and feature classifier. In this study, features such as density, size and shape are taken into account in the segmentation of microaneurysm. Fluorescence angiography was used as a data set, and thus its performance is limited to the resolution of these images [29]. Ege et al. [7] defined a tool for automatic analysis of digital retina images. Bayes classifier, Mahalanobis classifier and K-Nearest Neighbor (KNN) classifier were analyzed using different features such as minor and major axis variance. Although Bayes classifier and KNN classifier yielded promising results, it was also stated by the authors that a preprocessing step including mean filtering and thresholding was needed for a healthy classification process. When small microaneurysms removed during filtering and changes in background density are taken into consideration, it can be argued that the proposed method is not solely effective in the detection of microaneurysms.

Niemeijer proposed a new hybrid approach by combining the methods proposed by Spencer and Frame in order to increase performance. However, the disadvantage of this method is its duration of process, which takes 15 min and is a fairly long duration for image processing systems [22]. Fleming detects microaneurysms using contrast normalization on fundus images. However, this method requires the prediction of other lesion boundaries, which leads to a low value of sensitivity and specificity [8]. Gardner et al. used convolution neural network (CNN) to segment diabetic fundus images into 20*20 sub-images and detect microaneurysms in these images. This method needs a high amount of training data and duration [10]. Another study detected microaneurysms using characteristics defined by local and profile features for a KNN based classification [32].

C. Sinthanayothinin detected microaneurysms and hemorrhage by removing retinal structures such as optical disk and fovea and using recursive region growing algorithm. Therefore, the segmentation performance of the study was limited to the detection of other anatomic structures on the retina. The sensitivity and specificity in the segmentation of microaneurysms and hemorrhage was calculated as 77.5% and 88%, respectively [27]. In a study which classified microaneurysms using nearest neighbor method after various features of microaneurysm such as shape, size and greyness were obtained, it was underlined that the performance of this method greatly varied depending on the image quality since small vascular regions were not segmented [16]. Contrast enhancement and segmentation in images are important steps in the process, and optimization techniques can be used in these processes. Methods such as artificial bee colony, artificial ant colony, grey wolf algorithm and firefly algorithm are important examples, and can be applied to different image types.

In the present study, the performance of ant colony algorithm in the segmentation of microaneurysm was analyzed. Ant colony algorithm, which is an optimization method, may sometimes function more efficiently in image processing compared to conventional segmentation methods. For instance, the performance of edge detection algorithm is related to image characteristics, while the performance of thresholding

method is limited by the level of noise in an image [1]. On the other hand, when parameters such as the number of ants and iterations are accurately selected, it is possible to perform successful segmentation in ant colony algorithm irrespective of image characteristics. The microaneurysm segmentation performance of the proposed algorithm in color fundus images was compared with five different conventional methods (watershed, max. entropy, region growing, K-means, random walker). Microaneurysm images manually detected by a specialist eye doctor and automatically segmented microaneurysm images were analyzed based on Dice and Jaccard similarity indexes in order to identify the efficiency of the method on these images. Section 2 describes the data set and theoretical framework of the proposed method. Section 3 presents empirical studies and obtained performance values following preprocessing and segmentation. Section 4 discusses the obtained performance values and results of the proposed study.

The hypothesis

Microaneurysms are accepted as the most important clinical finding in the diagnosis of diabetic retinopathy (DR). In addition, the number and intensity of microaneurysms in different quadrants on the retina are important in grading the DR. Computer-based automated systems are very successful in accurately and effectively detecting microaneurysms that are difficult to detect in the early stages of diabetic retinopathy. Among the methods used in these computers based automated systems, optimization methods can be more successful than traditional image processing techniques. For example, the performance of the edge detection algorithm is related to the image characteristic, while the performance of the thresholding method is limited by the noise in the image. In this study, automatic detection of microaneurysms in the early stage of diabetic retinopathy was performed using the ant colony algorithm as an optimization method.

Material and methods

Material

Fundus images used in the present study were taken from Messidor and Diaretdb1, two different open access data sets [5,18]. Messidor contains 1200 pieces of images in TIFF format obtained from three different eye clinics. 588 of these images are 1440×960 pixel^2, 400 of

them are 2240 pixel$^2 \times 1488$, and 212 of them are 2304×1536 pixel^2. Diaretdb1 consists of images with lesions such as microaneurysm and exudate tagged by 4 different eye specialists. The flow diagram of automatic segmentation process in the present study is shown in Fig. 2.

Frangi filter (Vessel extraction)

Frangi algorithm is based on taking multi-scale second order derivative (Hessian matris) of an image. Density rapidly changes on the edge transitions of an image, which leads a large second order derivation in these regions. The vascularity of the related region is measured by taking all eigenvalues of Hessian matrix into account, which are calculated by taking second order partial derivatives horizontally, vertically and diagonally. As a result, small tubular geometrical shapes can be detected in an image. Because the size of vessels often vary, a measurement tool which changes in a certain range is defined [9]. The method is mathematically defined as follows:

$$F(x) = max_\sigma f(x, \sigma) \tag{1}$$

Here, x denotes the position of the pixel in the image, f represents the filter used for vessel extraction, and σ is the standard deviation of Gauss function used to take second order derivative of the image. Hessian matrix is calculated by taking second order partial derivatives horizontally, vertically and diagonally. A two-dimensional Hessian matrix is defined as follows:

$$H = \begin{pmatrix} H_{xx} & H_{xy} \\ H_{yx} & H_{yy} \end{pmatrix} \tag{2}$$

Here, H_{xx}, H_{xy}, H_{yx}, H_{yy} are directional second order partial derivatives of the image. Eigenvalue of H matrix (λ_1 λ_2) is used to measure vascularity value of a vessel by calculating neighborhoods of an x pixel belonging to the vessel. The equation of the filter is given in Eq. (3).

$$|\lambda_1| < |\lambda_2| \tag{3}$$

$$f(x) = \begin{cases} 0, & \lambda_2 > 0 \\ e^{-\frac{R_b^2}{2\alpha^2}}\left(1 - e^{\frac{S^2}{2\beta^2}}\right), & elsewhere \end{cases} \tag{4}$$

$$F(x) = max_\sigma f(x, \sigma)$$

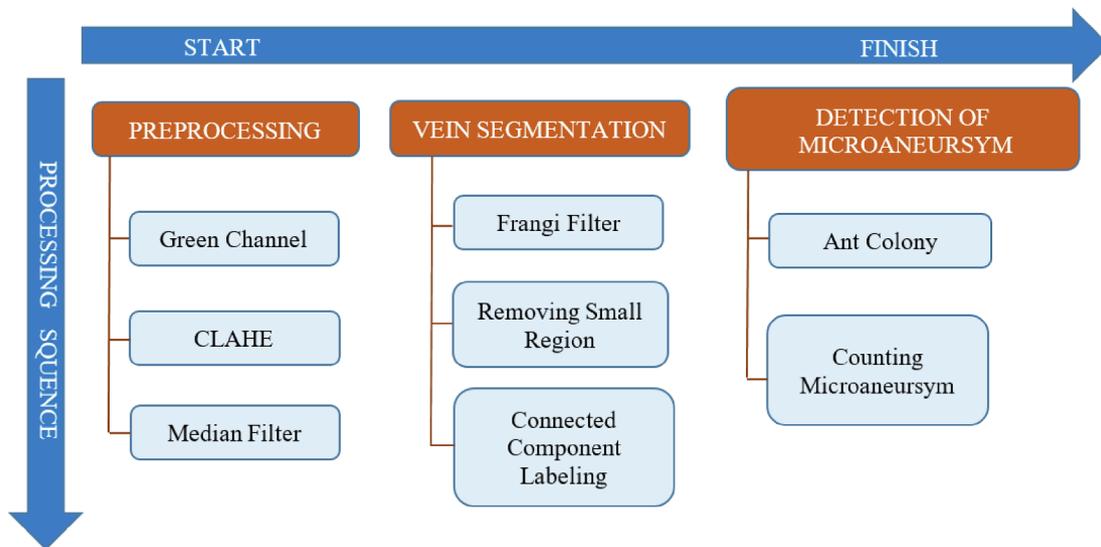Here, R_b is a parameter used to distinguish between straight lines

Fig. 2. Flow diagram of the automatic segmentation process.

from circular structures, while S^2 is used to remove background noise. α and β values are parameters used to determine filter sensitivity. The steps of the method are summarized in Algorithm 1.

Algorithm 1: Pseudo code for Frangi filter

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1. Read the image.
2. Specify α and β value.
3. Specify a maximum standard deviation value (σ_{max}).
4. Obtain Heisan matrix for each $\sigma < \sigma_{max}$ value.
5. Obtain λ_1 and λ_2 eigenvalues. Specify λ_2 so as to make $|\lambda_1| < |\lambda_2|$.
   6. Obtain $R_b = \frac{|\lambda_1|}{|\lambda_2|}$ and $S = \sqrt{\lambda_1^2 + \lambda_2^2}$ values.
7. Obtain fx values.
8. Specify maximum value of f(x) as F(x) filter function.

Ant colony (Detection of Microaneurysms)

In recent years, scientific communities have focused on analyzing and understanding different animal groups' collectively intelligent behaviors such as insects. Techniques used by these animals for communication among themselves or reaching a source of food are modelled and widely used in various scientific disciplines such as optimization problems [11,31]. Therefore, optimization algorithms named after animals which inspired them were developed by scholars. One of these algorithms is ant colony algorithm. Introduced by Dorigo et al., this method was applied to optimization problems such as travelling salesman problem (TSP), was inspired by the logic which ants follow to reach a source of food. Ants were created to use the shortest path to their source of food. In addition, they also have the ability to sense and adapt to environmental changes around themselves [4]. In this way, they are able to quickly find a new short path when the path they follow is not the shortest one. As shown in Fig. 3, ants follow a straight path in order to reach their source of food at the beginning. After pheromone, which is a chemical substance, is deposited as an obstacle to their path, other ants are made to follow the same path. Pheromone is used as a means of communication and navigation in the colony, and represents the information about the shortest path to be followed. The path followed by ants in case of an obstacle between their source of food and nest is shown in Fig. 3.

When ants encounter an obstacle on their path, they randomly choose one of two paths because they cannot follow pheromones. Because the amount of pheromones deposited on the shorter path in unit time will is high, the number of ants which will follow that path will also increase. Thus, the path between ants' source of food and nest will be updated. Ant colony algorith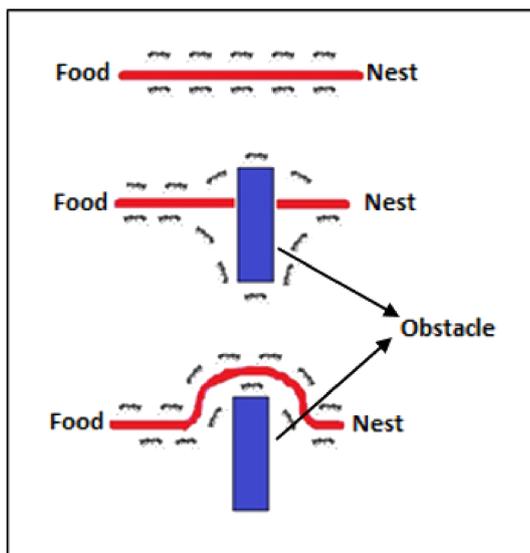m was inspired by ant colonies' this behavior. However, the functioning of artificial ants in the algorithm differs from that of natural ants. It is assumed in this algorithm that artificial ants possess a memory and that they are not totally blind and work in a discrete time period. Ant colony algorithm is also used for image segmentation processes such as object edge detection [30,21]. It can be argued that this algorithm offers superior functions compared to conventional image segmentation methods such as edge detection, region growing and thresholding. These methods, too, display successful results in image segmentation. But, different characteristics of images limit the advantages of these methods. For example, edge detection method may yield unclear or discrete edges depending on the nature of the images. Region growing may eliminate this problem; however, it may also leads mis-segmentation regions outside the object in question. Thresholding method may display inaccurate results in noisy images. On the other hand, ant colony method is an ideal method for image processing due to its discrete and parallel functioning. It succeeds in various processes such as image matching, image segmentation and tissue classification [20]. This method is used image segmentation by assuming that artificial ants exists on certain pixels in a given image. In addition, changes in intensity in the neighbor of a pixel yield a pheromone matrix representing information about the edge on that coordinate [12]. Images were divided into 128*128 sub-images in order to reduce processing time. Because this method is iterative, the number of ants and pheromone matrix is updated in each iteration.

In order to find the most optimal solution (edges of an object), it is assumed that k number of ants move along an I sub-image with a dimension of M_1*M_2 where each pixel is considered as a node. The method is summarized in Algorithm 2.

Algorithm 2: Pseudo code for Ant Colony filter

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1) Specify filter parameters and load input image.
2) For each 128*128 image window;
a) Place k number of ants on random positions and create the first pheromone matrix (τ^0)
b) Step index values for n = 1:N
   i) Ant index values for k = 1:K
   1. Take L number of steps for each kth ant and create probability transition matrix p(n) (with a dimension of M1M2*M1M2)
   2. Update local pheromone matrix
   i) Finish
   ii) Update general pheromone
   iii) Finish
3) Convert pheromone matrix to the size of input image.
4) Finish

In ant colony algorithm, artificial ants select their path with equal probability and complete their first tour in the iteration. Therefore, in each path is an equal amount of pheromone trail. Afterwards, it is increased in an amount which is inversely proportional to the length of the path that each ant follows. Thus, pheromone is updated for all paths based on the number of tours and length of the path. Ants select their path depending on the pheromone density of their path in neighbor

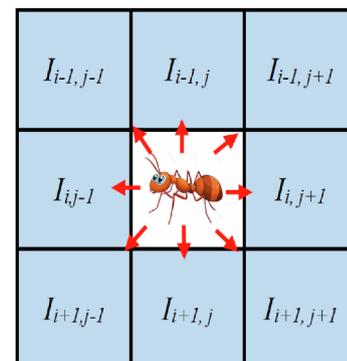Fig. 3. The path which ants follow between their nests and source of food.

Fig. 4. The position of ants on the image.

pixels (Fig. 4). The formulation of the path is given in Eq. (5).

$$f(x) = \begin{cases} \frac{[\tau(i,j)]^\alpha * [\eta(i,j)]^\beta}{\sum_{u j_k(i)} [\tau(i,u)]^\alpha * [\eta(i,u)]^\beta}, & iff j \in J_k(i) \\ 0, & elsewhere \end{cases} \quad (5)$$

In this equation;

$J_k(i)$ represents the points that an ant can reach at i.
$\tau(i, j)$ is the amount of pheromone between i and j.
$\eta(i, j)$ denotes the selectability parameter and inverse of the distance between i and j.
α and β represent adjustable parameters. Here, each ant updates pheromone matrix by walking around each pixel. $\tau(i, j)^n$ is the amount of pheromone on (i,j) pixel in Nth iteration, and pheromone matrix is updated as follows:

$$\tau(i, j)^n = (1 - w) * \tau(i, j)^n + w \tau(init) \quad (6)$$

Here, $w \in (0 1]$ is pheromone decay coefficient, and $\tau(init)$ is the initial amount of pheromone. All ants thus determine local pheromone values to determine general pheromone matrix.

$$\tau(i, j)^n = (1 - \rho) * \tau(i, j)^{n-1} + \rho * \sum_{k=1}^{k=N} \Delta\tau(i, j)^k \quad (7)$$

Experimental results

Preprocessing

Since retinal images are low contrast images with different levels of brightness, it is a difficult task to segment lesions such as micro-aneurysm and exudate. Therefore, a preprocessing step is needed for image enhancement. In the present study, contrast limited adaptive histogram equalization method [23] was applied to green channel of color (RGB) fundus image as a preprocessing step in order to increase image contrast. The reason why channel image green was employed is related to the fact that microaneurysms are more visible in this channel. In the last step of preprocessing, median filter was used to remove noises. It can be clearly seen in Fig. 5 that enhanced retinal images in the preprocessing increased the visibility of microaneurysms as a circular small dot.

Segmentation and removal of retinal vessels

Since the intensity of the retinal vessels similar to microaneurysms, have a dark-colored appearance, it is often difficult to segment them. Therefore, extraction and removal of retinal vessel structure is another important step to increase the segmentation performance. Frangi filter was used for this purpose. This method is based on calculating Hessian matrix, and is used to segment tubular structures on the image. Thus, it is possible to see cylindrical structures on the image to extract and remove. The segmented vessels using Frangi filter is shown in Fig. 6.a Because there are regions that do not contain a vessel, morphological processes (opening-closing) were used to remove unnecessary pixel groups (Fig. 6.b).

Detection of microaneurysms

Microaneurysms are dilations that appear as a result of thinning in peripheral blood vessels. Therefore, they are circular in shape and have a dark red color. Since retinal images contain regions with different levels of brightness due to their structure, the performances of conventional methods such as thresholding and edge detection are often limited by the brightness of the region in question, which remarkably influences the performance in image with a low level of brightness. Therefore, ant colony algorithm was used as an optimization method in order to eliminate the need for characteristics such as brightness and contrast in the segmentation of microaneurysms. At this stage, retina image was divided into 128*128 pixel^2 microaneurysm sub-images in
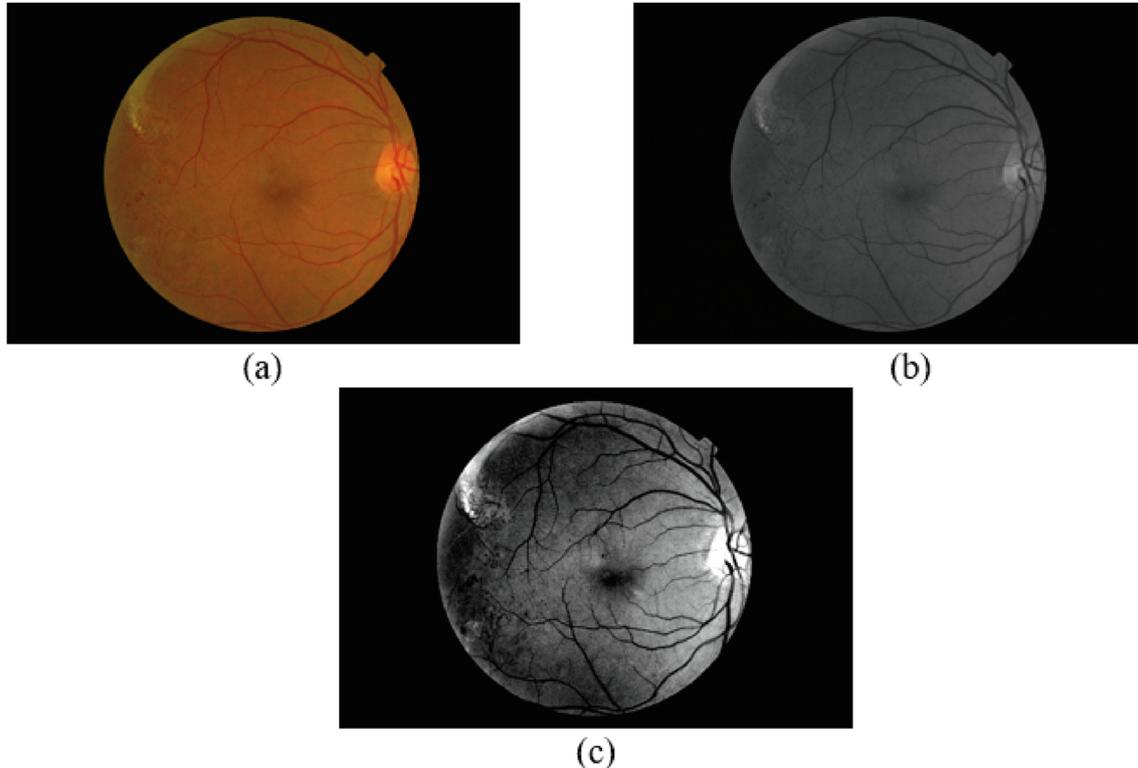

Fig. 5. Increasing the visibility of dark regions in the retina through preprocessing a. Color retina image (RGB) b. green channel image, c. adaptive histogram equalization. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
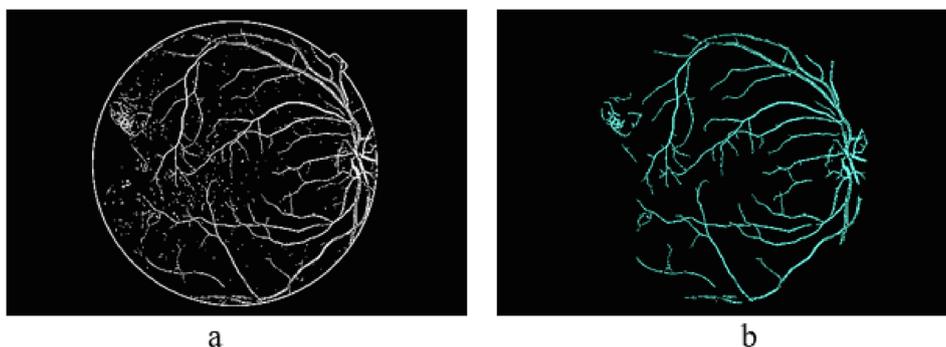
Fig. 6. Vessel extraction using Frangi filter a. Thresholded image after Frangi b. Removal of unnecessary small regions.

order to decrease processing time. These sub-images were selected to be within the retinal boundaries. Ant colony algorithm was applied to each sub-image. As shown in Fig. 7.a, microaneurysms in a color fundus image are seen in yellow in 128*128 pixel^2 sub-images in Fig. 7(b–d). Because vessels in the related sub-image had been segmented using Frangi algorithm, they were highlighted in red. The whole retina image was obtained after these sub-images had been integrated, and microaneurysms on retina surface were highlighted in green in Fig. 7. Ant colony algorithm used in the present study was proposed as a new approach in the automatic segmentation of microaneurysms which are difficult to detect in early diagnosis of DR. It is of vital importance to measure the efficiency of this approach in the early diagnosis of microaneurysm. Therefore, microaneurysms in early DR were segmented using five different algorithms as maximum entropy, watershed, region growing, k-means and random walker, and their performances were compared with that of ant colony algorithm. The basic principles of these well-known and widely used methods in image segmentation are summarized and details are given by cited the related references.

In maximum entropy method, an image is divided into two regions as front and back based on a threshold value. Later, the entropy of each region is calculated separately. This step is iterated for each threshold value, and the threshold value at which maximum entropy value is obtained is accepted as the optimal threshold value [24]. Watershed transformation is based on the resemblance between an image and a topographic surface. In such a surface, pixels with a high grey level are

accepted as tops of the ridges, whereas pixels with a low grey level are accepted as basins. Because the method performs segmentation based on the similarity among grey levels of pixels, it depends on the gradient of the original image. Because a gradient image contains many local minimums, an excessively segmented image consisting of numerous basins emerges, which is acknowledged as the greatest disadvantage of watershed transformation [3]. In random walker method, an image is considered as a graph model, and pixels in the image are represented by nodes. These nodes are interconnected after they are weighted based on the similarities among grey levels of pixels. Pixels previously selected as seed points by the user are considered as tagged pixels, while other pixels are considered as untagged pixels. The algorithm starts to function by assuming that a person randomly walks from an untagged pixel to other tagged pixels. This walker's probabilities during their first arrival at tagged pixels depending on edge weigths among pixels, i.e. nodes, are calculated. According to the obtained probability values, the (seed) value of the first tagged pixel at which the walker most probably arrived is given to the untagged pixel where the random walker has started. All untagged pixels are tagged in this way, and the image is divided into two classes as foreground and background [13]. In region growing process, a region is created on the image based on previously specified common features, which is usually the grey level of pixels in the related region. In this method, it is analyzed whether neighboring pixels of the region bear previously specified features. If pixels with same features exist, those pixels are added to the related region for
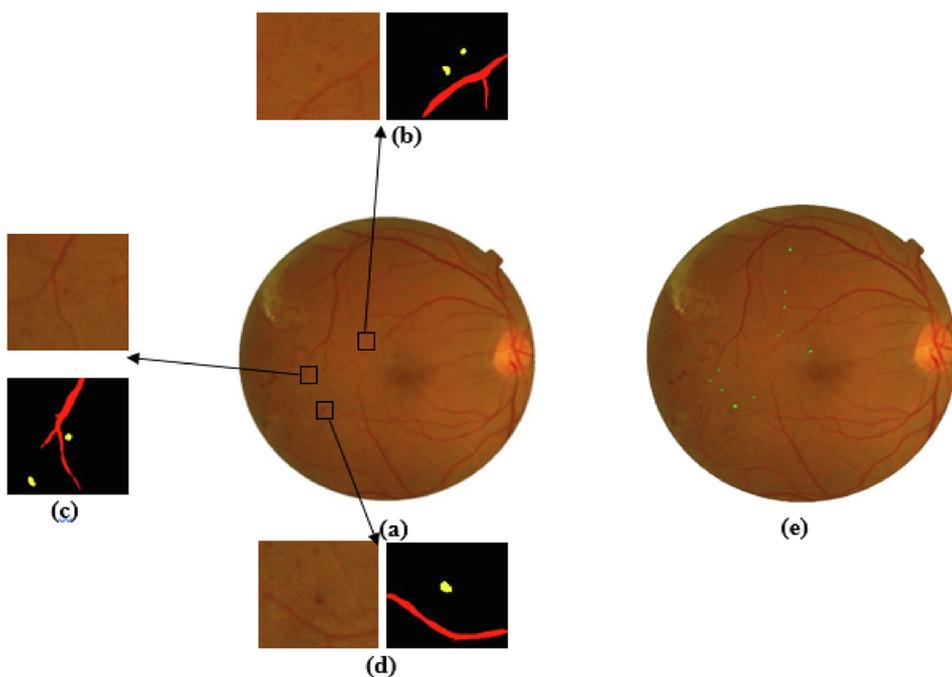

Fig. 7. Microaneurysms in an image from Messidor data set; a) Color fundus image, b), c) and d) 128*128 sub-images and segmented blood vessels and microaneurysms, e) Segmented microaneurysms highlighted as green colored holes in the original fundus image. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
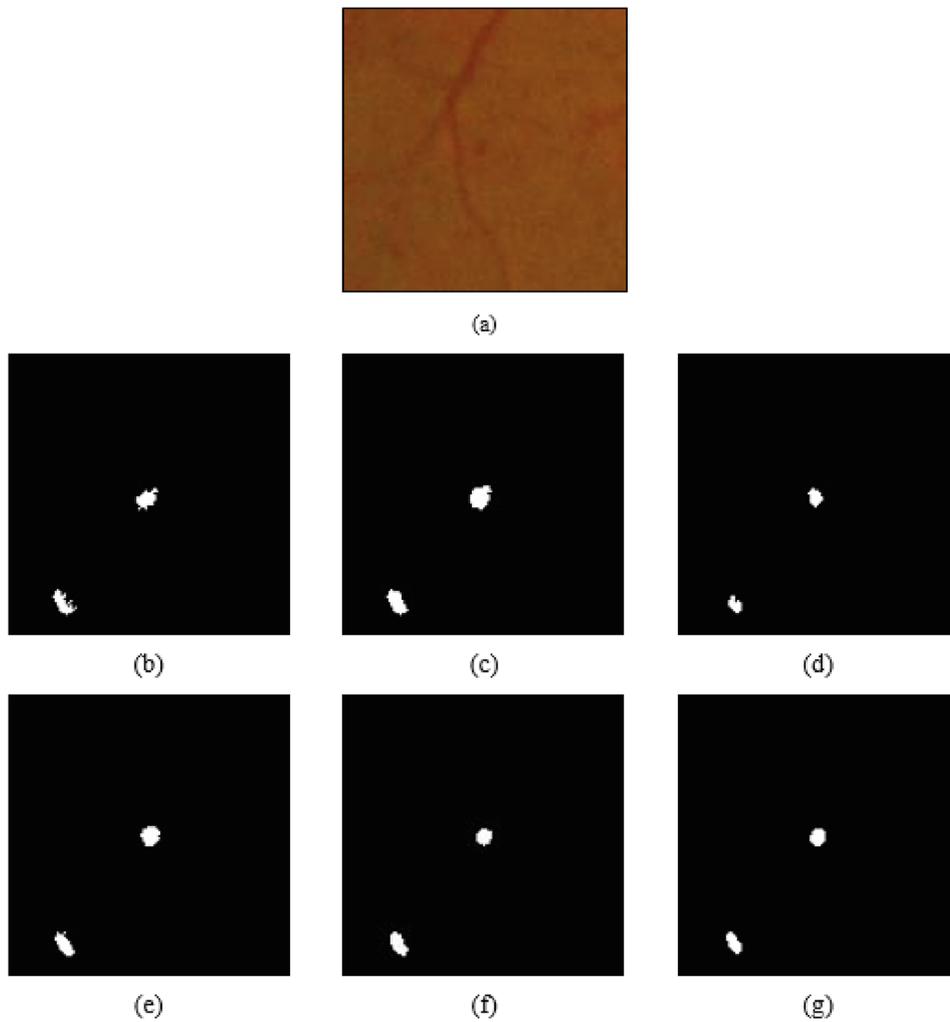
Fig. 8. Automatically and manually segmented (ground truth) microaneurysms. a. Original image, b. Watershed, c. K-Means, d. Random walker, e. Region growing, f. Ant colony, g. Ground truth.
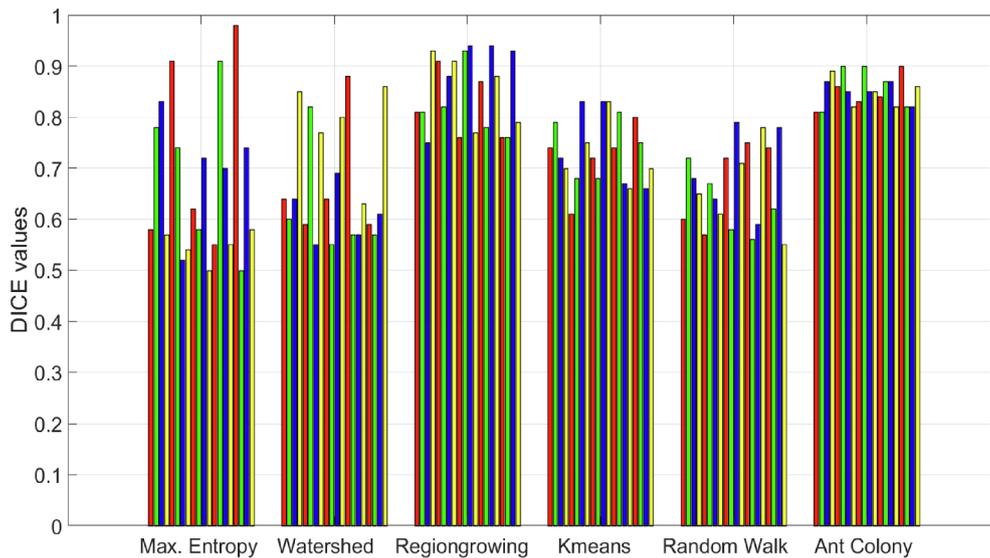

Fig. 9. Dice similarity index values.

region growing process, which continues until no pixels can be added [26]. In the present study, seed points were manually selected. Thus, it is possible to mention a semi-automatic segmentation. In K-Means method, pixels in an image are divided into n number of clusters which contain a single pixel based on their grey level. The number of clusters is previously specified, and each cluster has a randomly selected central

grey level. Pixels are integrated into a cluster if they are closer to its central grey level. After all pixels are clustered in this way, mean grey level in that cluster is calculated, and a new cluster center is found. As a result, a new clustering is performed based on this new cluster center, and pixels in the whole image are grouped based on the number of clusters, which results in the segmentation of the related regions [17]. Microaneurysms automatically segmented using the above-mentioned methods and manually segmented by a specialist eye doctor are shown in Fig. 8.

Performance measurements

Accurate detection of microaneurysms bears importance for the early diagnosis of diabetic retinopathy. In this respect, fundus images from Messidor and DiaretDB1 dataset containing early microaneurysms which are difficult to manually detect were used to test the performance of the proposed method in the segmentation of microaneurysms. These images were divided into 128*128 pixel^2 sub-images containing microaneurysm for analysis. The ant colony algorithm method proposed for the segmentation of microaneurysms were compared with five different algorithms (maximum entropy, watershed, region growing, random walker and k-means) to assess the performance of the method in these images. Microaneurysms manually detected by a specialist eye doctor were superimposed over automatically segmented microaneurysm images. Overlapping images were tested based on Dice and Jaccard similarity indexes, and performance values of 20 randomly selected sub-images are shown in Figs. 9 and 10.

It can be understood from Fig. 9 that performance values of maximum entropy vary between 0.52 and 0.98. It can be observed that only one image scored 0.98, while Dice index values remained lower than 0.7. As for other methods, Watershed has a Dice index value between 0.55 and 0.88, regiongrowing between 0.75 and 0.94, K-means between 0.55 and 0.78, random walker between 0.66 and 0.83, and ant colony between 0.81 and 0.90. It can be noted in Fig. 10 that Jaccard index values, too, displayed similar results.

When Dice and Jaccard index values are analyzed together, it can be argued that changes in performance values depending on the image quality are minimized in the proposed ant colony algorithm. However, changes in these index values are obtained in a wider range in other methods compared to ant colony.

It is stated in the existing literature that similarity index values

Table 1
Statistical values for Dice and Jaccard.

	DICE			JACCARD		
	Mean	Mode	Range	Mean	Mode	Range
Max. Entropy	0.67	0.58	0.48	0.66	0.57	0.47
Watershed	0.67	0.57	0.33	0.66	0.56	0.32
Region growing	0.79	0.75	0.19	0.77	0.74	0.18
K-means	0.66	0.72	0.24	0.66	0.71	0.23
Random walker	0.73	0.83	0.22	0.73	0.82	0.21
Ant Colony	**0.85**	**0.82**	**0.09**	**0.84**	**0.81**	**0.08**

higher than 0.7 are successful [25,2]. Table 1 shows the statistical values (mean, mode and range) for Dice and Jaccard indices. Range value is to see the change in performance, the mode is used to see which performance value is often achieved. It can be clearly seen that the highest mean Dice value (0.85) and Jaccard value (0.84) belong to the proposed ant colony algorithm. On the other hand, the second highest Dice (0.79) and Jaccard (0.77) values were obtained by region growing algorithm. When range values are analyzed, the change in the performance of region growing algorithm depending on the image contrast is 0.19, while the same value is 0.09 in ant colony algorithm, indicating that region growing based segmentation is insufficient for low contrast images. On the other hand, it can be observed that the changes in image quality did not significantly affect the segmentation performance of ant colony algorithm and that this method could accurately detect microaneurysms without being affected by image contrast.

Changes in maximum entropy result from that fact that entropy values of the segmented sub-images in question were not decisive. Because watershed method was applied to the gradient of the image, it caused unnecessary edge pixels and over-segmentation. In K-means and random walker methods, performance decreases in low contrast images as it usually depends on changes in the image contrast. Because a semi-automatic segmentation in which seed points were manually selected was performed in region growing method, accurate selection of seed points directly influence the performance of the method. On the other hand, the proposed ant colony based segmentation method obtained index values higher than 0.8 even in low quality images, demosntrating that the proposed ant colony algorithm remarkably succeeds in the segmentation of microaneurysms in color fundus images and that it can
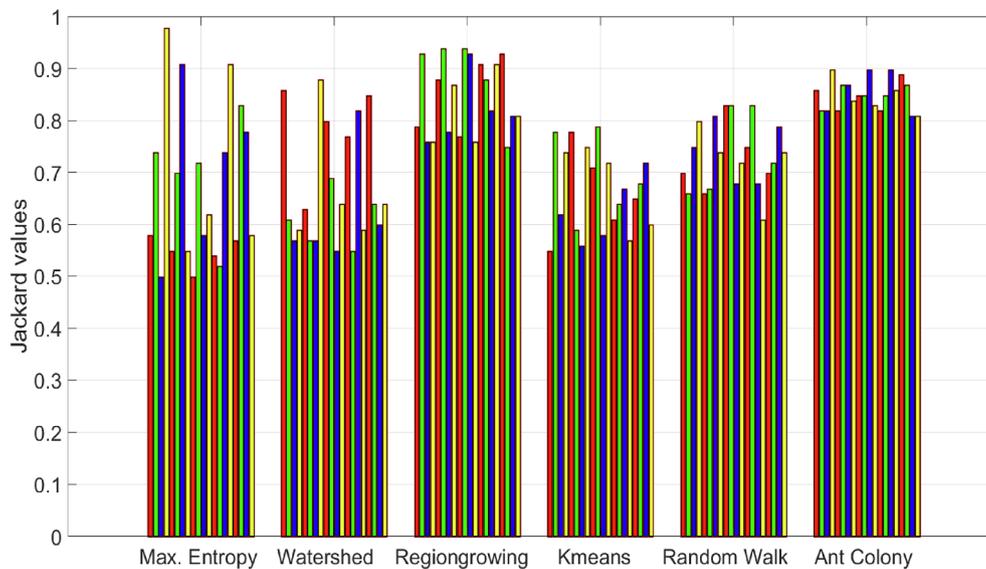

Fig. 10. Jaccard similarity index values.

be used as a decision support system in early diagnosis.

Discussion

The existence of microaneurysms on retina surface is acknowledged as an important clinical finding in the diagnosis of DR. Therefore, accurate detection of these lesions is of vital importance for a better diagnosis and treatment. To this aim, the present study performed the ant colony based segmentation of microaneurysms which are difficult to manually detect in early diagnosis of DR. First, the methods used in the studies on the related topic and their performances regarding the detection of microaneurysms were analyzed. In addition to conventional image segmentation techniques used in the segmentation of lesions such as microaneurysm that appear as particles on the image, ant colony algorithm as an optimization method was proposed for image segmentation. Conventional segmentation methods may sometimes fail to detect objects on an image. For instance, the performance of edge detection approach decreases if the number of boundary pixels similar to edges is high, and the performance of thresholding decreases if the amount of noise is high in an image. Although the ant colony algorithm was followed by region growing algorithm in terms of segmentation performance, manual selection of seed points and semi-automation pose threats to the performance of this method. It is actually possible to automatically select seed points using different techniques in this method. However, this will also lead to some difficulties depending on the characteristics of the image such as contrast. Although the ant colony algorithm based segmentation method proposed in the present study, which has not been so far used in the literature, needs a long duration of process, it was demonstrated that it could perform accurate segmentation in low quality fundus images irrespective of image characteristics.

Conclusion

In the present study, an ant colony based method was proposed for automatic segmentation of microaneurysms, which is considered as an important clinical finding in the early diagnosis of DR in fundus images. The study is first based on the retinal vessel extraction and detection of existing microaneurysms on the retina surface. Thus, it was made possible to easily segment microaneurysms which had the same level of brightness as vessels. In addition to image processing techniques and clustering methods, ant colony algorithm, which is an optimization method, was also used for the segmentation of microaneurysms. It was thus possible to reveal the performance of optimization methods in the segmentation of images in the data set used for the present study. The developed software superimposed automatically segmented microaneurysm images over those manually detected by a specialist eye doctor, and was tested using Dice and Jaccard similarity indexes. The results show that the traditional methods commonly used in the literature are highly sensitive to image contrast in the segmentation of microaneurysms. This causes a decrease in performance in low contrast images. On the other hand, it was observed that the ant-colony-based early diabetic retinopathy detection system did not affect the image contrast in the detection of microaneurysms and showed a more stable performance. It can be concluded that the presented study will make easier the early diagnosis of diabetic retinopathy thanks to accurate detection of microaneurysms even in low quality images. The obtained results may be lead to further studies in this field with a new point of view.

Declaration of Competing Interest

None.

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