Multilevel Segmentation of Fundus Images using Dragonfly Optimization

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ABSTRACT
This paper presents a self adaptive dragonfly optimization (DFO) based methodology for performing multilevel segmentation of colour fundus images. The multilevel segmentation problem is formulated as an optimization problem and solved using the DFO. The method optimizes the threshold values for each of the three chromatic channels of colour fundus images through effectively exploring the solution space in obtaining the global best solution. The results of two fundus images illustrate the performance of the developed method.

General Terms
image processing, segmentation

Keywords
fundus images, multilevel segmentation.

1. INTRODUCTION
Retina is the inner part of human eye that senses the outside illumination. Light falls on retina and millions of opto-sensitive tissues convert these signals into electric signals and relay these signals to the brain for interpretation. Optical disc appears as an elliptical bright region on retinal fundus image, where all retinal blood vessels enter the retina. The pattern of blood vessels in retina are unique to a specific person which is important from the perspective of biometric analysis [1].

Diabetic retinopathy is the one among other main reasons of blindness in the adult population. Early discovery of diabetic retinopathy through screening programs and successive treatment is critical in order to avoid visual blindness. The early signs of diabetic retinopathy as manifested in retinal images include micro-aneurysms, hemorrhages and exudates. Clinicians commonly use retinal images for the screening differential diagnosis of retinal diseases such as retinal edema, diabetic retinopathy, age-related macular degeneration, malarial retinopathy, glaucoma, cataracts, exudates, lesions, prediction of strokes in hypertension patients and so on [2-4].

The increasing pervasiveness of diabetes and low number of clinical specialists, increase the need for automatic methods to reduce the workload on physicians [5] besides making the diagnosis robust and consistent. Color fundus imaging has emerged as the preferred procedure by the medical community for comprehensive large-scale retinal disease screening due to their ease of acquisition and good visibility of retinal structures [6].

In the literature, a number of methods for segmenting the optical disk, blood vessels, exudates, cataracts, etc have been suggested [7-12]. Most of these methods consider the gray level representation or a single color plane in segmenting the fundus images, rather than taking into account the multiple color channels of fundus images. For instance , the contrast enhanced L channel of L*U*V* color spaces has been used to apply morphological operations as well as H-maxima transform for detecting exudates in [7]. The gray level image has been thresholded to segment optic disc and exudates in retinal images in [10]. A geometrical model of vessel structure involving gray scale image has been suggested for detection of optic disc in retinal images in [11]. In [12], the grey level version of the color original image has been used to segment the optical disk on two of the three different approaches presented: multi-thresholding and active contour without edges.

It is well known fact that the segmentation of color image demonstrates to be more useful than the segmentation of gray scale image, because color image expresses much more image features than gray scale image. In fact, each pixel is characterized by a great number of combination of R, G, B chromatic components. The segmentation of fundus images would have been more effective, if segmentation is performed considering the rich chromatic information in all the three color channels of fundus images. However, it requires the computational cost considerably higher than that needed for gray scale image, but it is no longer a major problem with the increasing speed of computation. In fact, there has been a remarkable growth of techniques for the segmentation of color images in this decade [13, 14].

Recently, a dragonfly optimization (DFO), a population based meta-heuristic optimization algorithm that simulates the static and dynamic swarming behaviors of dragonflies [15], has been applied for performing multilevel segmentation of gray scale images [16]. The multilevel segmentation problem has formulated as an optimization problem and solved using the DFO. The method optimizes the threshold values through effectively exploring the solution space in obtaining the global best solution.

The focus of this paper is to develop a multilevel thresholding based method for segmenting the fundus images in RGB colour space by modifying the DFO based gray scaled segmentation method. The paper is organized with four sections containing introduction, proposed method (PM), results and discussions, and conclusion.

2. PROPOSED METHOD
The threshold-based methods assume that an image is composed of regions with different intensity ranges. The optimum threshold values are determined by the histogram of the image which has the valleys between two adjacent peaks [16]. Owing to its simplicity, histogram thresholding is a widely used technique for gray scale image segmentation. But it is not a trivial job for color image because of its multi-dimensional structure [13, 14]. The PM is an extension of the

segmentation method suggested by the authors in [16] with a view of processing the R, G, B chromatic components of fundus images. The median filter is applied for noise removal.

The proposed method involves representation of decision variables and formation of a fitness function.

Table 1 Results for Fundus Image-1

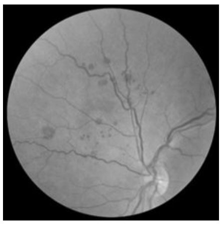
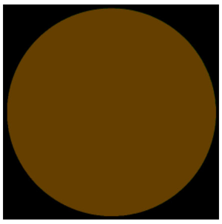
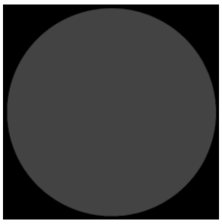
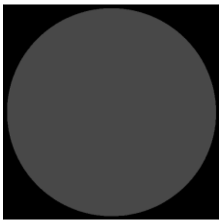
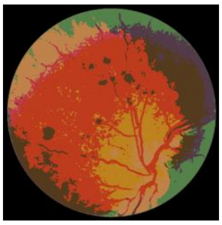
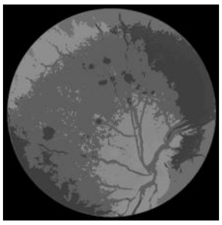
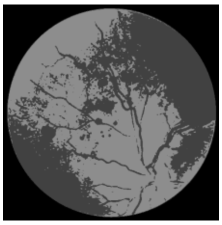
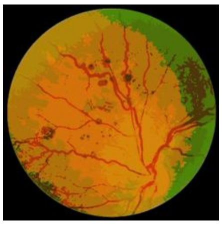
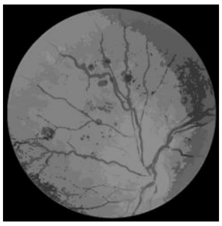
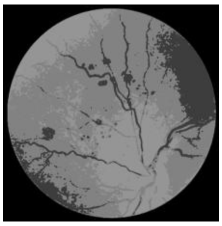
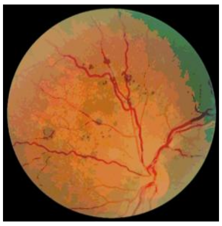
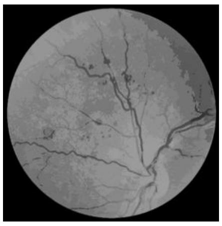
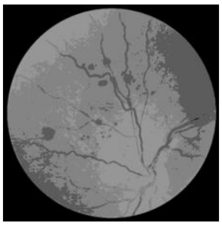
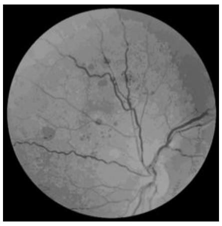
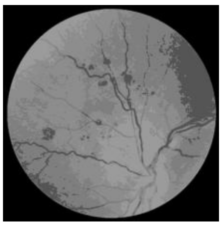
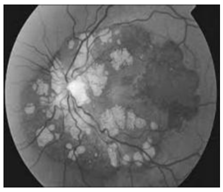
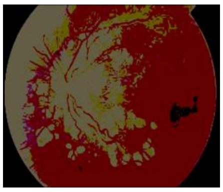
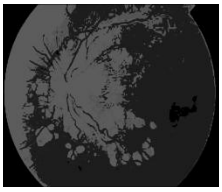
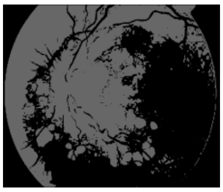
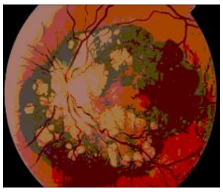
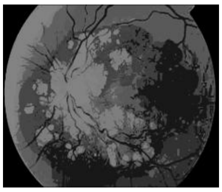
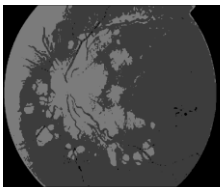
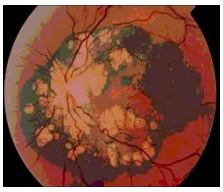
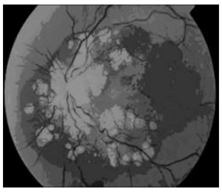
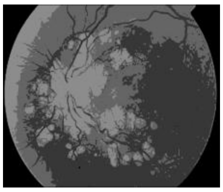
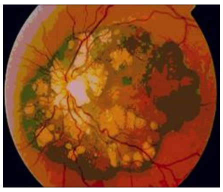
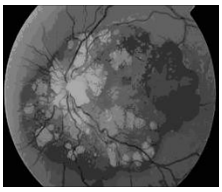
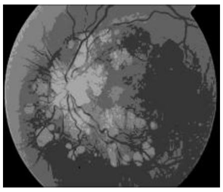
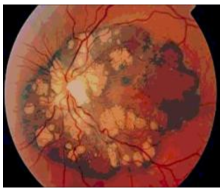
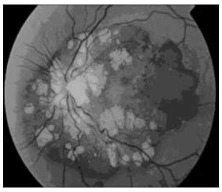
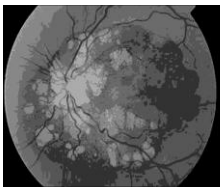
		Fundus image in RGB colour Space		Gray scale converted fundus image	
					
Level	Threshold values	Segmented Colour Image	Segmented Colour Image in Gray Scale	Threshold values	Segmented Gray Scale Image
2	100 63 150			72	
3	84 190 59 130 30 74			65 141	
4	78 176 211 53 114 134 10 117 197			61 130 149	
5	70 157 189 216 47 105 124 141 26 58 70 87			30 92 132 150	
6	35 109 164 193 218 43 99 118 130 146 25 59 72 88 136			26 85 127 141 155	

Table 2 Results for Fundus Image-2

		Fundus image in RGB colour Space		Gray scale converted fundus image	
					
Level	Threshold values	Segmented Colour Image	Segmented Colour Image in Gray Scale	Threshold values	Segmented Gray Scale Image
2	98 93 68			103	
3	81 165 68 118 62 105			60 123	
4	78 155 198 44 81 125 45 72 115			55 101 140	
5	72 139 168 203 43 77 112 156 14 17 110 159			54 97 128 166	
6	68 129 156 180 209 42 73 99 128 169 40 57 76 103 143			50 86 107 135 171	

Each chromatic channel of RGB fundus image is divided into nc number of classes by $nc-1$ number of thresholds of $\{T_1, T_2, \cdots, T_{nc-1}\}$. These thresholds act as separators between the consecutive classes of $\{C_1, C_2, \cdots, C_{nc}\}$ in the range of threshold values of $\{[0, \cdots, T_1], [T_1+1, \cdots, T_2], \cdots\cdots, [T_{nc-1}+1, \cdots, L]\}$ for each chromatic channel, where L is the maximum pixel intensity value of the digital image. In the PM, each dragonfly df is defined to denote the threshold levels of all the three colour spaces and the self-adaptive parameters as decision variables as

$$df = \left\{ \begin{array}{l} T_1^R, T_2^R, \cdots, T_{nc-1}^R, \\ T_1^G, T_2^G, \cdots, T_{nc-1}^G, \\ T_1^B, T_2^B, \cdots, T_{nc-1}^B, \\ s_i, a_i, c_i, f_i, e_i, \gamma_i, \omega_i \end{array} \right\} \quad (1)$$

The SADFO searches for optimal threshold values by maximizing a fitness function F . based on Kapur's entropy.

$$\text{Maximize} \quad F = \sum_{colour \in R,G,B} \left\{ \sum_{k=1}^{nc} H_k^{colour} \right\} \quad (2)$$

Where H_k^{colour} represents $k-th$ entropy of the selected colour channel of RGB image and is evaluated by

$$\left.\begin{array}{ll}
H_1^{colour} = \sum_{i=0}^{T_1^{colour}} \frac{p_i}{\chi_1} \ln\left(\frac{p_i}{\chi_1}\right) \quad ; & \chi_1 = \sum_{i=0}^{T_1^{colour}} p_i \\
H_2^{colour} = \sum_{i=1+T_1^{colour}}^{T_2^{colour}} \frac{p_i}{\chi_2} \ln\left(\frac{p_i}{\chi_2}\right) \quad ; & \chi_2 = \sum_{i=1+T_1^{colour}}^{T_2^{colour}} p_i \\
\vdots & \vdots \\
\vdots & \vdots \\
H_{nc}^{colour} = \sum_{i=1+T_{nc-1}^{colour}}^{L} \frac{p_i}{\chi_{nc}} \ln\left(\frac{p_i}{\chi_{nc}}\right) \quad ; & \chi_{nc} = \sum_{i=1+T_{nc-1}^{colour}}^{L} p_i \\
 & colour \in \{R, G, B\}
\end{array}\right\} \tag{3}$$

p_i^{colour} represents probability distribution at $i-th$ intensity level of the selected chromatic channel of RGB image and is calculated by

$$p_i^{colour} = \frac{h_i^{colour}}{np} \; ; \quad i \in \{0, 1, \cdots, L\} \; ; \; colour \in \{R, G, B\} \tag{4}$$

h_i^{colour} indicates number of pixels that corresponds to $i-th$ intensity level of the selected chromatic channel of R, G and B.

np is the total number of pixels in the image.

χ_i denotes the probability of set C_i

An initial swarm of dragonflies is obtained by generating random values within their respective limits. The fitness function F is calculated by considering the threshold values of each dragonfly; and the exploration and exploitation phases, which represent social interaction of dragonflies in navigating and searching for foods and avoiding enemies, are performed for all the dragonflies in the swarm with a view of maximizing their finesses. The iterative process is continued till convergence [16].

3. RESULTS AND DISCUSSIONS

The PM has been tested on two fundus images. As the images are rectangular shaped with different sizes, the width of these images is adjusted to have 512 pixels and the height is proportionally altered with a view to have the true shape of the images. The software package is developed in Matlab platform and executed in a 2.67 GHz Intel core-i5 personal computer. The results of the PM are compared with that of the gray scale based existing method (EM) suggested in [16] with a view of studying the performances.

The results for threshold levels of 1, 2, 3, 4 and 5 are obtained and presented in Table 1 and 2. These table also include the original RGB and gray scale converted fundus images. The threshold values for the PM are given in second column of the tables, while for the EM, they are given in the fifth column of the tables. It can be observed that the segmented colour image, given in third column of the table, conveys more accurate information than that of the segmented gray image given in the last column of the table. The segmeted colour images are also converted into gray scale images and presented in fourth column of the tables. The visual comparison of gray scale images of the PM with those of the EM also ensures that the PM is able to make better segmentation. The visual analysis of these results clearly indicate that the segmented results are better with more number of threshold levels.

4. CONCLUSIONS

DFO is a population based optimization algorithm that simulates the static and dynamic swarming behaviors of dragonflies. A self adaptive DFO based methodology for performing multilevel segmentation of colour fundus images has been presented. The multilevel segmentation problem has been formulated as an optimization problem and solved using the self adaptive DFO. The method has been applied on two fundus images with a view of illustrating the performances. It has been found from the results that the PM effectively yields better segmented results than that of performing segmentation after converting the image into gray scale. The method can be modified to classify various retinal diseases such as retinal edema, diabetic retinopathy, age-related macular degeneration, malarial retinopathy, glaucoma and cataracts, exudates.

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