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 components 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 gray 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

<table>
<thead>
<tr>
<th>Level</th>
<th>Threshold values</th>
<th>Fundus image in RGB colour Space</th>
<th>Gray scale converted fundus image</th>
<th>Segmented Colour Image</th>
<th>Segmented Colour Image in Gray Scale</th>
<th>Threshold values</th>
<th>Segmented Gray Scale Image</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>100 63 150</td>
<td><img src="image1" alt="Segmented Colour Image" /></td>
<td><img src="image2" alt="Segmented Colour Image in Gray Scale" /></td>
<td></td>
<td>72</td>
<td></td>
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<tr>
<td>3</td>
<td>84 190 59 130 30 74</td>
<td><img src="image3" alt="Segmented Colour Image" /></td>
<td><img src="image4" alt="Segmented Colour Image in Gray Scale" /></td>
<td></td>
<td>65 141</td>
<td></td>
<td></td>
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<tr>
<td>4</td>
<td>78 176 211 53 114 134 10 117 197</td>
<td><img src="image5" alt="Segmented Colour Image" /></td>
<td><img src="image6" alt="Segmented Colour Image in Gray Scale" /></td>
<td></td>
<td>61 130 149</td>
<td></td>
<td></td>
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<tr>
<td>5</td>
<td>70 157 189 216 47 105 124 141 26 58 70 87</td>
<td><img src="image7" alt="Segmented Colour Image" /></td>
<td><img src="image8" alt="Segmented Colour Image in Gray Scale" /></td>
<td></td>
<td>30 92 132 150</td>
<td></td>
<td></td>
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<tr>
<td>6</td>
<td>35 109 164 193 218 43 99 118 130 146 25 59 72 88 136</td>
<td><img src="image9" alt="Segmented Colour Image" /></td>
<td><img src="image10" alt="Segmented Colour Image in Gray Scale" /></td>
<td></td>
<td>26 85 127 141 155</td>
<td></td>
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<tr>
<td>Level</td>
<td>Threshold values</td>
<td>Segmented Colour Image</td>
<td>Threshold values</td>
<td>Segmented Colour Image in Gray Scale</td>
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<tr>
<td>2</td>
<td>98, 93, 68</td>
<td><img src="image1.png" alt="Image" /></td>
<td></td>
<td><img src="image2.png" alt="Image" /></td>
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</tr>
<tr>
<td>3</td>
<td>81, 165, 68, 118, 62, 105</td>
<td><img src="image3.png" alt="Image" /></td>
<td></td>
<td><img src="image4.png" alt="Image" /></td>
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<tr>
<td>4</td>
<td>78, 155, 198, 44, 81, 125, 45, 72, 115</td>
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<td><img src="image6.png" alt="Image" /></td>
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<tr>
<td>5</td>
<td>72, 139, 168, 203, 43, 77, 112, 156, 14, 17, 110, 159</td>
<td><img src="image7.png" alt="Image" /></td>
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<td><img src="image8.png" alt="Image" /></td>
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<tr>
<td>6</td>
<td>68, 129, 156, 180, 209, 42, 73, 99, 128, 169, 40, 57, 76, 103, 143</td>
<td><img src="image9.png" alt="Image" /></td>
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<td><img src="image10.png" alt="Image" /></td>
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</table>

Each chromatic channel of RGB fundus image is divided into \( n_c \) number of classes by \( n_c-1 \) number of thresholds of \( \{ T_1, T_2, \ldots, T_{n_c-1} \} \). These thresholds act as separators between the consecutive classes of \( \{ C_1, C_2, \ldots, C_n \} \) in the range of threshold values of \( \{ 0, T_1, T_1+1, \ldots, T_{n_c}, T_{n_c}+1, \ldots, L \} \) 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

\[
df = \begin{bmatrix}
T_1^B, T_1^G, T_1^R, \\
T_2^B, T_2^G, T_2^R, \\
\vdots, \\
T_{n_c-1}^B, T_{n_c-1}^G, T_{n_c-1}^R
\end{bmatrix}
\]

The SADFO searches for optimal threshold values by maximizing a fitness function \( F \) based on Kapur’s entropy.

\[
\text{Maximize } F = \sum_{k=1}^{R,G,B} \left[ \sum_{i=1}^{L} \frac{H_k^{\text{color}}}{i} \right]
\]

Where \( H_k^{\text{color}} \) represents \( k-th \) entropy of the selected colour channel of RGB image and is evaluated by
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.

5. ACKNOWLEDGMENTS

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6. REFERENCES


