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Segmentation of Optic Disc and Optic Cup Using Krill Herd Algorithm for the Assessment of Glaucoma

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Abstract

Glaucoma is an eye disease that results in irreversible loss of vision. The early detection of glaucoma helps to prevent the vision loss. So, there is a need to develop a fast and efficient algorithm for disease prediction. Several clustering algorithms are encountered for segmentation of retinal fundus images. The existing method used K-means clustering algorithm for the glaucoma detection but it was significantly sensitive to the initial randomly selected cluster centres. Inorder to overcome this drawback the Krill Herd (KH) algorithm was implemented to obtain the optimal clusters. The diagnosis of Glaucoma can be done through measurement of Cup to Disc Ratio (CDR), it is calculated after determining the optic disc and cup boundary. The normal cup to disc ratio ranges from 1.1 to 1.3. If the cup to disc ratio exceeds 1.3 then it indicates the abnormal condition that is the presence of glaucoma. The performance results of proposed algorithm is compared with Region Growing algorithm and Active Contour algorithm. The proposed method is tested with collected database images which contain 1000 images with an accuracy of 96%.

***Keywords*:** Cup to Disc ratio, glaucoma, Krill Herd algorithm, segmentation

INTRODUCTION

The eye is one of the most sensitive organs of the human body. There are many diseases that can affect the eye including those diseases that can damage the optical disk. These disease results in several types of retinopathy in the retina such as diabetic retinopathy, non-proliferative diabetic retinopathy, proliferative diabetic retinopathy, hypertensive retinopathy, arteriosclerotic retinopathy and retinopathy of prematurity. Glaucoma is a potentially blinding disease that affects approximately 80 million persons worldwide by 2020 [1]. It is the second leading cause of blindness. Glaucoma is a chronic and irreversible neuro degenerative ocular disorder in which the optic nerve head is progressively damaged, leading to deterioration in vision and quality of life [2]. Glaucoma is commonly asymptomatic. The patients are usually ignorant about it until a noticeable visual loss occurs at a later stage, giving rise to its nickname the 'silent thief of sight'. Over a period of 5 years, the optic nerve fiber loss progression in glaucoma can range from 9% to 63% [3]. Ophthalmologists use three principal methods to detect onset of glaucoma. The first approach is the assessment of increased intraocular pressure inside the eye. However, this is not sensitive enough for early detection and glaucoma can sometimes occur without increased eye pressure. The second approach identifies field of abnormal vision with specialized equipment which makes it unsuitable for a comprehensive screening of glaucoma except in sophisticated medical centers. The third approach is evaluation of damage to the optic nerve. This is most reliable but requires a trained professional, is time-consuming, expensive and highly subjective. Expert assessment may vary depending on experience and training [4].Most of the methods are able to locate only the OD in retinal images. These methods do not discuss about the segmentation of the OD region and take large computation time to locate only the OD.

RELATED WORKS

OD segmentation: Active contours based approach is commonly used to segment optic disc contour as done , but segmentation results are not very good because of uneven illumination and noise[7]. Optic disc localization is required in these algorithms as preliminary step. Employed a global elliptical parametric model combined with a local variable edge strength dependent stiffness model to identify the OD contour. Hough transform is also a popular method for OD boundary segmentation in fundus images[8]. Employed the Hough transform based method for optic disc boundary segmentation. Localization and segmentation of OD is presented using circular and parabolic Hough transform by used OD boundary detection using circular Hough transform after rough estimation of OD center and morphological processing[9] [10][11] .

OC segmentation: OC segmentation is restricted to the region inside OD. Since, OC is largely characterized by a discontinuity in the depth of the retinal surface, proposed solutions either rely on explicit depth measurement or depth cues derived from appearance of the CFI. In the former approach, depth is obtained from OCT or from stereo-based disparity maps [16][17].

In this paper a new algorithm is proposed for automatic segmentation of the OD in retinal image. This algorithm achieves superior accuracy for OD detection, yields better performance for OD segmentation and low computation time to segment the OD over the existing methods reviewed in literature.

MATERIALS AND METHODS

The algorithm proposed in this paper segments the optic disc and optic cup using Krill Herd algorithm and compared the performance results with other state of the art methods by using Seed based region growing and Active Contour Segmentation.

(a) Seed based Region growing Segmentation

The seed based region growing is partitioning of an image into similar areas of connected pixels through the application of similarity criteria among candidate set of pixels. Each of the pixels in a region are same with respect to some characteristics such as color, intensity and texture. The segmentation of optic disc is performed by Region growing algorithm where OD is the brightest part in the image. Pixels having highest intensity correspond to optic disc and exudates. Therefore pixels having highest intensity are chosen as initial seed points. At each step the region is then grown from these seed points to adjacent points depending pixel intensity. Eight connected neighbourhood is considered for pixel adjacent relationship. The region is iteratively grown by comparing all unallocated neighbouring pixels to the region. The steps involved in region growing algorithm are,

Step1. Choose initial seed points.

Step2. Check the neighbouring pixels and add them to the region if they are similar to the seed.

The selection of a set of seed points is the primary step in region growing. This selection is based on user criterion (for example, pixels in a certain graylevel range).The exact location of the seed points is the beginning of the initial region. The seed points are grouped into regions A1, A2…An. Let T be the set of unallocated pixels which border one of the regions. At each step algorithm takes one of the pixels from T and consider all its 8 neighbours, N(x) added the pixels to one of the regions with which neighbours of the pixel intersect. The next step is to examine all pixels from N(X) and calculate distance from their neighbouring regions. The distance is consider as the distance between pixels and its neighbouring region. If pixels have more than one neighbour and calculate the distance from all its neighbouring regions and add it to the region to which it is the closest. The minimal distance from its neighbouring region as,

$$\partial(z) = \min_{x \in T} \left\{ \partial(x) \right\} \tag{1}$$

Repeat step 2 for each of the newly added pixels, stop if no more pixels can be added.

Region growing algorithm has the following advantages,

- It can correctly partition the regions having same properties
- Provides the original images with clear edges
- Its concept is very simple. It requires only a small numbers of seed point
- It is possible choose multiple criteria at the same time
- It performance is good with respect to noise

(b) Active Contour Segmentation

The active contour is initiated by pre-processing the fundus image where the boundary of the optic disk is first approximated automatically. This approximation enables placement of initial points of the active contour surrounding the optic disk. Such a mechanism is useful in the applications where large number of retinal images in a database need to be processed to remove the optic disk because the automated approximation of the optic disk avoids manual placement of initial control points of the active contour. This stage can be divided into several sub-stages, namely, pre-processing, extraction of blood vessels and approximate detection of the optic disc. Pre-processing involves noise removal using Gaussian filtering. The process for the approximation of the optic disk boundary is the second process out of the stated four main processes. Approximation of the optic disk is essential prior to actual detection of the boundary because the optic disk does not always exist in the same position within retinal images.

After removal of noise, the blood vessels and the approximate location of the optic disk need to be extracted using an edge detection algorithm [22].The selection of the Kirsch operator is due to several reasons. First and foremost, the optic disk has a circular shape. This means, edges are present in all directions and as such, the edge detection method must be capable of extracting such edges in each and every direction.

The Kirsch operator extracts both blood vessels and the optic disk in retinal images. As such, these blood vessels need to be removed in order to isolate and segment only the optic disk. This process mainly consists of three sub processes, namely, application of median filter, filling of holes and morphological opening.

The mathematical framework of the Active contour is given as follows:

A retinal grey-scale image I is defined in the image $x-y$ plane, with $I(x,y)$ denoting the value of luminance at position (x,y).An active contour is defined as a parametric curve $v(s)=[x(s)y(s)]$ in the plane, with s as a normalised parameter representing a position on the curve; $s\in[0,1]$ and $v(s)$ depends on time [23].

The total energy of an active contour, E_{snake} defined as,

$$E_{snake}=\int_0^1 E_{snake}(v(s))ds \tag{2}$$

If *Eint* and *Eext* represent the internal and external energy of the snake, respectively, *Esnake* can be written as:

$$E_{snake}=\int_0^1 E_{Int}(v(s))+E_{Ext}(v(s))ds \tag{3}$$

Where

$$E_{Int}=\frac{1}{2}(\alpha(s)\left|\frac{d}{ds}v(s)\right|^2+\beta(s)\left|\frac{d^2}{ds^2}v(s)\right|^2) \tag{4}$$

(c) Krill Herd Algorithm

Krill Herd (KH) algorithm is one of the most recent swarm based algorithms simulating the herd behavior for each krill individual. It was introduced in order to solve function benchmark problems. KH algorithm works to find the minimum distance of the krill individual from pixels with the highest intensity. KH algorithm has been successfully applied in many optimization areas such as numerical optimization, electrical and power system neural network breast cancer detection and graph based network route.

The krill herd (KH) algorithm is one of meta-heuristic techniques. It is used to solve global optimization problems based on the simulation of the herd behavior for krill individuals. Krill positions are updated according to the three motion effects as the following:

a. Movement induced by other krill individuals

b. Foraging activity

c. Random diffusion

The objective function of the KH algorithm is the sensing distance, it is used to find the nearest high intensity pixel.

Lagrangian Model of the KH Algorithm

KH algorithm uses the Lagrangian model to be capable with the dimensionality of the search space. The decision space for each krill individual is generated as the following equation:

$$\frac{dX_i}{d_t}=F_i+N_i+D_i \tag{5}$$

Where, N_i is the motion affected by the other krill individuals, F_i is the foraging motion and D_i physical diffusion of the i^{th} Position.

The Motion Affected by Other Krill Individuals

The trend of the first movement a_i is estimated by the objective effect, local effect, and pixel intensity. For each position, the motion can be defined as the following equation:

$$N_i^{new}=N^{\max}a_i+a_i^{t\arg et} \tag{6}$$

Where, $a_i=a_i^{local}+a_i^{t\arg et}$ (7)

$N^{\max}$ is the maximum affected speed, ω_n is the intertia weight value for influenced motion between (0, 1) based on term similarity. a_i^{local} is the local effect and $a_i^{t\arg et}$ is the target effect .

RESULTS AND DISCUSSION

A database of 1000 fundus images from a local hospital has been used for experimentation and testing of proposed method. The database has retinal images with non-uniform illumination, bright and dark, low contrast, blurry images, choroid vessels and also has artifacts which occur during acquisition process. The proposed algorithm is competent enough to strategically segment the optic disc with exact boundaries. The doctors from the local hospital have marked the optic disc boundaries and these annotated images have been used to segment optic disc and optic cup, calculate the processing time, mean and standard deviation of optical disc area.

Optic Disc and optic cup Segmentation

In order to evaluate the performance of the proposed optic disc and optic cup segmentation method implemented through krill herd algorithm for segmentation. Figure 1 demonstrates input eye image considered for the segmentation of optic cup and optic disk of the image using Krill Heard Algorithm. The images are preprocessed by morphological operations. The KH algorithm is find the nearest optimal high intensity pixel for each krill individual, so the clustering has the same principle through each document to finding the nearest high intensity pixels. On the other hand, each document is going to find a more similar pixels to join it. The segmented optic disc and optic cup for the input image was shown in figure1.

Cup to Disc Ratio

The Cup to Disc Ratio (CDR) is measured in the green channel. It is defined as the ratio of height of the optic disc to height of the optic cup. The normal cup to disc ratio ranges from 1.1 to 1.3.Figure 1 shows that the detection of glaucoma level in input retinal image. Through the adaptation of proposed algorithm in figure 1 glaucoma level is computed the CDR value as 1.00871 which means value higher than 1.00 is resemblance of glaucoma persistent in an image and its level is starting stage of the glaucoma. The CDR value of 0.55511 in [30] is high as compared to normal CDR value shows that the level is an initial stage of glaucoma.

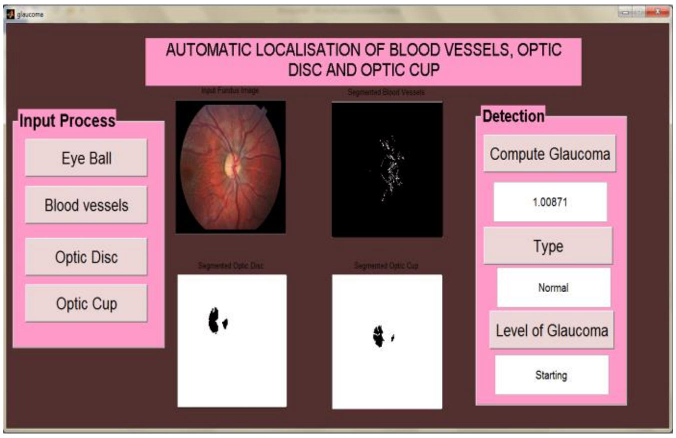

Figure 1: Glaucoma Detection

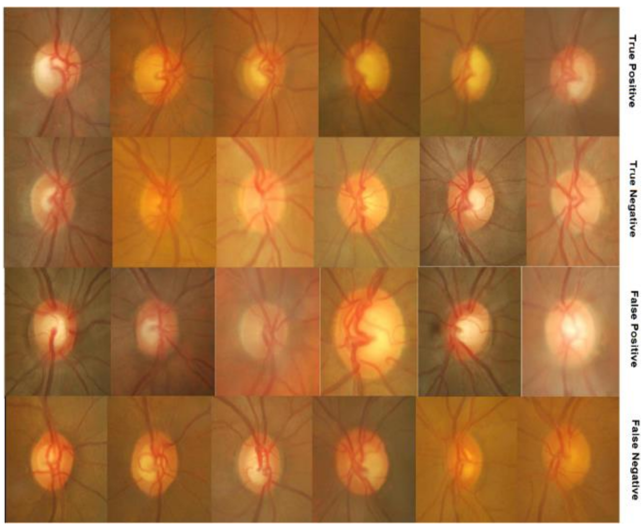

Figure 2: Performance analysis

The capacity of an algorithm to perform an accurate segmentation of optic cup region is measured by its Sensitivity (Sn) and its ability to determine the optic cup is expressed by its Specificity (Sp). Figure 2 shows the performance analysis on different input retinal images.

Average sensitivity indicates the average portion of the real OD area segmented by the automated algorithm. Higher value of the average sensitivity denotes the better segmentation.

$$\text{Sensitivity, } S_n = \frac{TP}{TP+FN} \times 100$$

Average specificity indicates the average portion of then on OD area segmented by the automated algorithm. Higher value of the average sensitivity denotes the better segmentation.

$$\text{Specificity, } S_p = \frac{TN}{TN+FP} \times 100$$

Accuracy signifies the percentage of images in a particular database where the OD is effectively recognized.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \times 100$$

Table 1 and figure 3 and figure 6 shows the performance measures of the proposed algorithm and compares it with other segmentation algorithms. The experimental results show that our method KH algorithm has successfully segment the optic disc with sensitivity and specificity of 90.69 and 99.94 respectively. This result is close to the state of the art published methods that are more complex. The accuracy of proposed method is 96% is high compared to the existing methods.

Average run time indicates the average time required to segment the optic disc for a particular database measured in nano seconds The average run time required to segment one retinal image is around 7 ns using an Intel Core N3050 CPU running at 1.60 GHz with 4 GB of RAM is less compared to 26.22s and 27.6s .

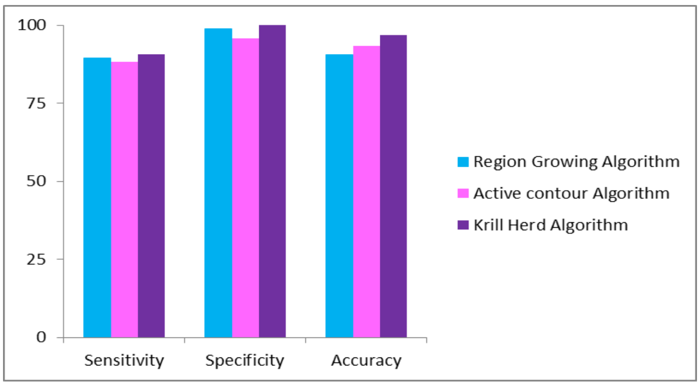

Figure 3: Performance analysis for optic disc segmentation

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Table 2 demonstrates the mean, standard deviation of optic disc area and run time required for segmentation of optic disc using the proposed and conventional methods. It is observed that the run time required for segmentation of optic disc using krill herd algorithm is minimum compared to conventional methods. Hence, the proposed method can be considered to be a significant development towards automated detection of optic disc from fundus images.

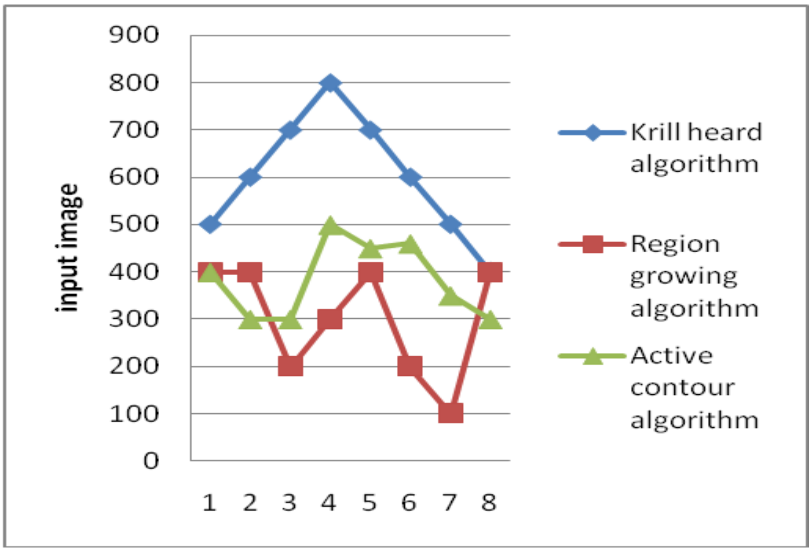

Figure 4: Runtime comparison of different input retinal images

Table 1: Performance comparison with state-of-the-art methods on the database

Algorithms	Sensitivity	Specificity	Accuracy
Region Growing Algorithm	89.58	98.9	90.46
Active contour Algorithm	88.37	95.8	93.29
Krill Herd Algorithm	90.69	99.94	98.20

Table 2: Comparison results of Region Growing, Active Contour and Krill Herd Algorithms

Input image	Region Growing Algorithm			Active Contour Algorithm			Krill Herd Algorithm		
	Optic Disc Area		Runtime(ns)	Optic Disc Area		Runtime(ns)	Optic Disc Area		Runtime(ns)
	Mean	SD		Mean	SD		Mean	SD	
1	2.249	21.99	10.5	0.58	0.49	22.7	6.52	19.3	6.23
2	4.99	31.82	10.6	0.60	0.48	19.4	8.17	22.73	6.30
3	5.85	35.33	11.5	0.59	0.49	22.2	9.48	28.06	7.00
4	10.33	47.45	14.5	0.60	0.48	26.8	11.9	33.17	10.2
5	20.85	66.66	13.4	0.66	0.47	22.2	14.5	39.65	9.38
6	21.96	68.9	11.5	0.55	0.49	27.4	19.7	45	7.00
7	47.71	95.20	9.80	0.67	0.46	19.6	21.3	53.77	5.00

CONCLUSION

Glaucoma is an evasive and dangerous eye disease and is the second leading cause of blindness globally. Since Glaucoma can not be cured, the diagnosis at their early stage can help clinicians to treat it accordingly and to prevent the patient from leading to the blindness. In this paper, the construction of a Krill herd algorithm for segmenting the optic disc and optic cup was demonstrated. The diagnosis of Glaucoma can be done through measurement of CDR. The normal cup to disc ratio ranging from 1.1 to 1.3. If the cup to disc ratio exceeds 1.3 then it indicates the abnormal condition that is the presence of glaucoma. Based on this the experimental results shows the input image is considered as starting stage of glaucoma affected fundus. It has shown that proposed algorithm is competitively faster and trustworthy. This algorithm has been tested on 1000 databases and has produced an accuracy of 96.8% with less computation time over the existing methods.

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