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SEGMENTATION OF RETINA -BASED ON FRACTIONAL PSO TECHNIQUE

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Abstract: Glaucoma is the third leading cause of blindness, characterized by gradual damage to the optic nerve and result in visual field loss. Particle Swam Optimization Algorithm is a recent meta heuristic that has been inspired from social behavior of fishes, bees, birds, etc, that live together in colonies. In this frame work, the segmentation process is constrained by two prior models; a shape prior model and a texture prior model. Furthermore, the particle swarm optimization algorithm is used to refine the preliminary segmentation according to the shape prior model. In this work, we tested the proposed technique for the segmentation scans and the obtained results show the efficiency of the proposed technique to accurately delineate the desired objects.

Keywords: PSO, DPSO, GLAUCOMA, SEGMENTATION

I. INTRODUCTION

Image segmentation is a difficult yet very important task in many image analysis or computer vision applications. Differences in the mean gray level or in color in small neighborhoods alone are not always sufficient for image segmentation. Rather, one has to rely on differences in the spatial arrangement of gray values of neighboring pixels - that is, on differences in texture [3]. In this work, we propose a fully automated medical image segmentation frame work. In this frame work, the segmentation process is constrained by two prior models; a shape prior model and texture prior model. Furthermore, the particles spam optimization is used to refine the preliminary segmentation according to the shape prior model. In this work, we tested the proposed technique for the segmentation scans and the obtained results show the efficiency of the proposed technique to accurately delineate the desired object. After configure the fractional-order Darwinian PSO algorithm and adjust the curve parameters according to the desired object, we carry out the segmentation process according to the following sequence:

1. Select the curve parameters randomly from the range specified and create the corresponding level set functions.
2. Segment the image by using the curves derived from the generated level set functions.
3. Measure the fitness of each curve by computing the fitness function and determined the best curve.
4. Update the curve parameters according to the fractional-order Darwinian PSO algorithm equations.

Matsui *et al.* were the first to publish a method for retinal image analysis, primarily focused on vessel segmentation Their approach was based on mathematical morphology and they used digitized slides of fluoresce in angiograms of the retina. In the following years, there were several attempts to segment other anatomical structures in the normal eye, all based on digitized slides. The first method to detect and segment abnormal structures was reported in 1984, when Baudoin *et al.* described an image analysis method for detecting microaneurysms, a characteristic lesion of diabetic retinopathy. Their approach was also based on digitized angiographic images. The work of Baudoin *et al.* detected microaneurysms using a "top-hat" transform, a step-type digital image filter .The field dramatically changed in the 1990s with the development of digital retinal imaging and the expansion of digital filter-based image analysis techniques. These developments resulted in a rapidly increasing number of publications that is continuing to expand. Closely related to retinal image analysis, the first multicenter, randomized clinical trials in the history of ophthalmology, the Diabetic Retinopathy Study and especially the Early Treatment of Diabetic Retinopathy Study, showed the relevance of the thickness of retinal structures.

II. GLAUCOMA

Glaucoma is the third leading cause of blindness, characterized by gradual damage to the optic nerve and resultant visual field loss. Early diagnosis and optimal

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treatment have been shown to minimize the risk of visual loss due to glaucoma .Glaucoma is primarily a neuropathy, not a retinopathy, and acts on the retina by damaging ganglion cells and their axons. The hallmark of glaucoma is cupping of the optic disc, which is the visible manifestation of the optic nerve head (ONH) 3-D structure. The optic disc can be imaged two-dimensionally either through indirect stereo biomicroscopy or with stereo color fundus photography. The ratio of the optic disc cup and neuroretinal rim surface areas in these images, called cup-to-disc ratio, is an important structural indicator for assessing the presence and progression of glaucoma. Glaucoma is typically treated with ocular pressure lowering drops, and in refractory cases through surgery.

III. CURRENT STATUS OF RETINAL IMAGING

Retinal imaging has developed rapidly during the last 160 years and is a now a mainstay of the clinical care and management of patients with retinal as well as systemic diseases. Fundus photography is widely used for population-based, large scale detection of diabetic retinopathy, glaucoma, and age-related macular degeneration. Optical coherence tomography (OCT) and fluorescein angiography are widely used in the diagnosis and management of patients with diabetic retinopathy, macular degeneration, and inflammatory retinal diseases. OCT is also widely used in preparation for and follow-up in vitreo-retinal surgery.

FUNDUS IMAGING

We define fundus imaging as the process whereby a 2-D representation of the 3-D retinal semi-transparent tissues projected onto the imaging plane is obtained using reflected light. Thus, any process which results in a 2-D image, where the image intensities represent the amount of a reflected quantity of light, is fundus imaging.

Since the retina is normally not illuminated internally, external illumination projected into the eye as well as the light reflected by the retina must traverse the pupillary plane. Thus the size of the pupil, the small opening in the iris usually between 2 and 8 mm in diameter, has always been the primary technical challenge in fundus imaging .Fundus imaging is complicated by the fact that the illumination and imaging beams cannot overlap because that results in corneal and lenticular reflections diminishing or eliminating image contrast. Consequently, separate paths are used in the pupillary plane, resulting in optical apertures on the order of only a few millimeters. Because the resulting imaging setup is technically challenging, fundus imaging historically involved relatively expensive equipment and highly trained ophthalmic photographers.

IV. PARTICLE SWARM PTIMIZATION

In the original PSO algorithm introduced by Kennedy and Eberhart the position and velocity of a particle is updated using equations (1) and (2)

$$vt+1 = vt + R1*C1* (g - xt) + R2 *C2 * (p - xt) \quad (1)$$

$$xt+1 = xt + vt+1 \quad (2)$$

where C1, and C2 are the "learning" constants, R1 and R2 are randomly generated numbers (from a uniform distribution) in the interval [0, 1], g is the position of the global best particle (i.e., the particle with the best value in the entires warm), and p is the position with the best value recorded by the particle so far. The computation of g involves an inspection of the values of all the other particles in the swarm.

V. PSO VARIANTS

Other modifications have been added to the PSO algorithm, aiming to improve its convergence. The most common variations correspond to modifications on the computation of the velocity. Equation (1) shows the original method for computing the velocity of a particle. Eberhart and Shi introduced the so-called Inertia Weight model in which the velocity of a particle at iteration t is multiplied by a constant parameter !, called Inertia Weight, before computing the velocity for iteration t + 1, as shown in equation (3).

$$vt+1 = !*vt + R1*C1*(g - xt)+ R2*C2*(p-xt) \quad (3)$$

The parameter ! helps to balance between exploitation and exploration. Although the parameter ! is maintained constant in this model, Eberhart andShi suggested that a linearly decreasing inertia weight may improve the convergence of the PSO algorithm. An initial !i and final !f values for the inertia are set, and the value of the inertia weight !t for the iteration t is computed using equation (4).

$$!t=!i-(!f-!i)*tT \quad (4)$$

where T is the total number of iterations and t = 0, . . . , T. . In the Constriction Factor model not only the velocity at iteration t is multiplied by a constant, but the new computed velocity is also affected, as shown in equation (5).

$$vt+1 = \_*[vt + R1]*C1* (g - xt) + R2 * C2* (p - xt)] \quad (5)$$

Only one component is used for the velocity update equation, as shown in equation (6) for the cognition only model and in equation (7) for the social only model.

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$$vt+1=vt+R *C * (p - xt) \quad (6)$$

$$vt+1=vt+R* C * (g - xt) \quad (7)$$

Both, the cognition and the social models have been used in combination with the Inertia Weight and the Constriction Factor models.

Use of Mutation

Probably the easiest approach to adapt PSO to deal with multimodal optimization problems is to add a mutation operator, such as those adopted with genetic algorithms. . If we have the chromosome of an individual represented as a vector of real numbers Ct = (c1, c2, . . . , cn) at the iteration t and ck is the gene to mutate, then the mutated value c′ k is computed as follows:

$$k = \_ck + \_(t,UB - ck) \text{ if } P < 0.5$$
$$ck - \_(t, ck - LB) \text{ otherwise} \quad (8)$$

where P is a randomly generated number in the interval [0, 1] with uniform distribution, LB and UB are the lower and upper bounds for the coordinate ck, respectively, and the function _(t, z) returns a value in the range [0, z]. The probability that _(t, z) returns a value close to zero must increase as t increases. The function proposed for that sake is:

$$(t, z) = z *1 - R(1- tT)b - \quad (9)$$

This is followed by process called Nic-Hing and clustering. This will provide good result

VI. RESULT

The below shown fig:a is the original fundus image. Here eye can be affected with many diseases such as cholesterol, diabetics, etc. This can be clearly seen in the segmented image. The segmentation will show how deeply diseases are affected. The output can be shown as

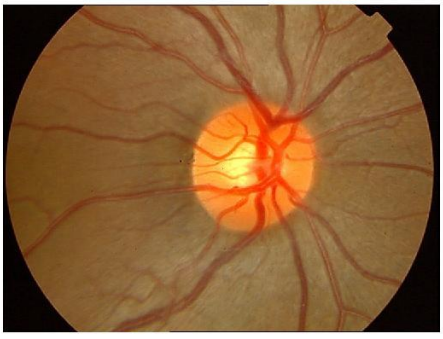

Fig:a (original image)

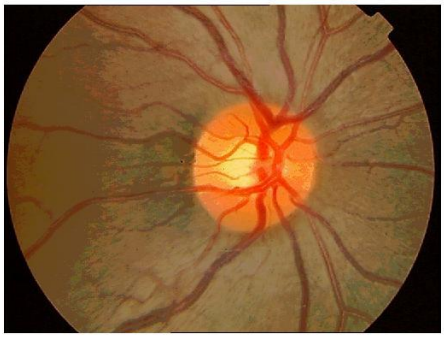

Fig:b(output image at level 5)

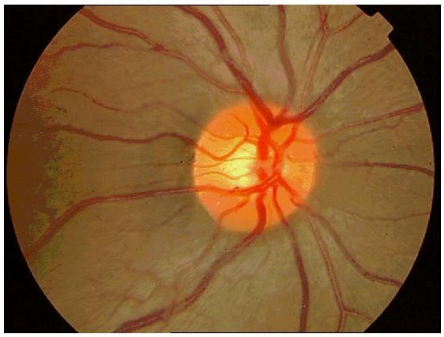

Fig:c (output image at level 3)

The level shows the colour difference.The segmented area can be clearly seen in fig:b and fig:c.

VII. CONCLUSION

We have presented a new method for image segmentation called PSO. This can be done in several steps.Here we doing segmentation for retinal part of eye. This is to check whether any diseases is affected to eye.Every disorder that occurring to our body will affect our eyes too.In the future process, we are going to do the automated segmentation.This will be faster than the above given method.

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