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Swarm Intelligence Techniques in Segmenting Human Retinal Vasculature

A. Anitha, T. Sridevi

Abstract*: *Vasculature of human retina furnishes information concerning various eye related ailments and also assists in lesions detection. Severity of the eye diseases can be discerned from pathological conditions related to changes in the retinal vasculature. In this work, for pre-processing, Contrast Limited Adaptive Histogram Equalization (CLAHE) and average filter is used to enhance the input image. Further, swarm intelligence techniques, Particle Swarm Optimization (PSO), Darwinian Particle Swarm Optimization (DPSO), Fractional Order-Darwinian Particle Swarm Optimization (FO-DPSO) are used in segmenting the blood vessels of the human retina. Additionally, similarity index metrics are employed in evaluating the accuracy of the retinal vasculature segmentation with ground truth. The results obtained clearly reveals that FO-DPSO outperforms in segmenting accurately than PSO and DPSO. Results of the segmentation are further reinforced using box and dendogram plot.

Index Terms*: *Segmentation, PSO, DPSO, FO-DPSO, Retinal Vasculature

I. INTRODUCTION

Expeditious acceleration in the advancement of computing technologies, machine learning algorithms have reinforced significance of automated medical diagnosis. Retina is an essential tissue in the body which expends extortionate level of nutrients and oxygen. A structured ophthalmic vasculature of retina is required for a good visual function [1]. Growth of the retinal blood vessels is influenced by several pathological conditions. Understanding the retinal vasculature in fundus images for the researchers and clinicians can prevent the retinal vascular disorders which include hypertensive retinopathy, Diabetic retinopathy, cardiovascular disorders, Diabetes mellitus and Retinal vein Occlusion. Diabetic Retinopathy and hypertensive retinopathy are the most common eye ailment entails automated computer assisted diagnosis. It is a persistent disorder that affects diabetic patients which alters the radial symmetry of blood vessels in retina. Discerning retinal blood vessel is a prime factor for early and accurate diagnosis of the disease intercepting the loss of vision.

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***** Correspondence Author

Dr .A.Anitha*, PG Department of Computer Science, D.G Vaishnav College, Chennai-600 106, India

Dr. T. Sridevi, PG and Research Department of Computer Science & Applications, D.G Vaishnav College, Chennai-600 106, India.

Segmentation of digital retinal fundus image significantly assists in diagnosing medical pathologies which includes high blood pressure, diabetes, coronary disorders [2]-[4]. It assists in evaluating the well-being of the eye. Retinal vasculature changes give important information in identification of these diseases. Image can be segmented in variety of ways, among these thresholding based methods [5]-[8] gained importance because of its effectiveness.

Researches contributed largely in segmenting the retinal blood vessels by employing variety of techniques for early diagnosis of eye related ailments. Automatic segmentation of vasculature with feature extraction relying on multi-scale features [9] in detecting blood vessels with varied height and width has been presented. New supervised neural network vessel segmentation was reported using gray level and moments invariant feature selection [10] which is efficient in DRIVE and STARE images. An ensemble classification model had designed for segmentation using Gabor filter responses; inclination analysis of gradient vector field, line strength has shown a considerable improvement in analyzing retinal blood vessels [11]. Gaussian Mixture Model (GMM) suggested by Roychowdary et al. defined a segmentation process of vessels as a three stage model with less segmentation time [12]. Issues related to segmentation in potts model or total variation was replaced by proposed fully connected conditional random field model using SVM [13]. Effective retinal blood vessel segmentation in diagnosing cardiovascular disease was suggested by tackling distortions present in the central vessel reflex [14]. Soorya et al had presented a retinal image diagnosis method in diagnosing glaucoma by identifying the first bend in the vessel from the segmented optic disk [15]. Similarly, variety of PSO based vasculature segmentation techniques have been initiated in the literature [16]-[21]. However, very few works has been carried out in comparing the efficiency of the image segmentation using PSO with its variants such as DPSO and FO-DPSO.

In this work, swarm intelligence techniques PSO, DPSO and FO-DPSO are pertained to segment the blood vessels of retina in STARE images. Effectiveness of the segmented image is assessed, compared and validated using the similarity measures in contrast with their ground truth.

II. METHODOLOGY

The work uses digital fundus images of retina acquired from Structured Analysis of Retina project [22] which is openly accessible. Images with heterogeneous size are converted to equal size (512 x 512) for analysis.

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Contrast and the edges of the retinal images are enhanced using CLAHE. Further average filter is enforced in enhancing the image. The enhanced images are segmented using swarm intelligence optimization techniques PSO, DPSO and FO-DPSO. The segmented blood vessels and ground truth of the images are correlated and their performance is assessed using various similarity metrics. Research framework of the work is characterized in Figure 1.

A. Particle Swarm Optimization (PSO)

PSO relies on optimization and designed following the emulation of communal behaviour of birds flocking in a swarm or fish schooling [23], [24]. PSO is initialized with set of randomly generated solutions (particles) which then explores for optimal solution by upgrading generations. Particle alters their

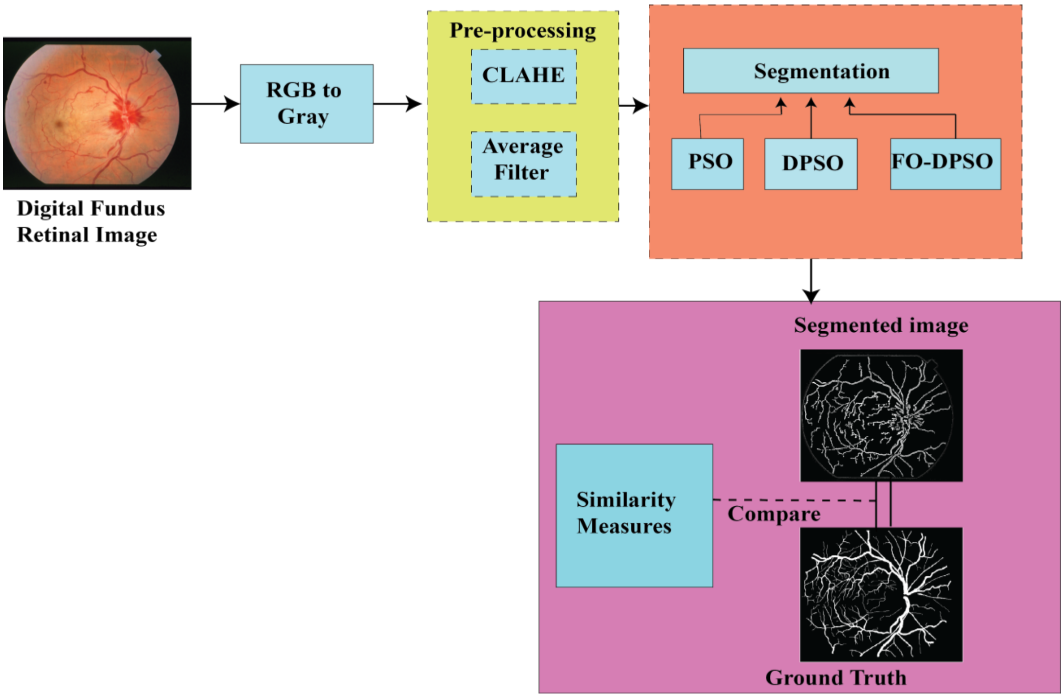


Figure 1: Research Methodology for Segmenting the Retinal Vasculature

position gliding in its search space by comparing its distance to the best particle of the swarm with its personal distinctive best position. Fitness function evaluates the performance of the particle considering its closeness with the global optimal solution. Let S^n be the n-dimensional search space, particle i glides through the search space then the particle personal best solution is upgraded as specified in equation 1,

$$p_i(t+1) = \begin{cases} p_i(t) & if\ f_n(c(t+1)) \geq f_n(p_i(t)) \\ c_i(t+1) & if\ f_n(c_i(t+1)) < f_n(p_i(t) \end{cases} \quad (1)$$

where, f_n represents the fitness function , t denotes the time and c_i is the particle present position.

If the particle global best position is denoted as g_b in equation 2,

$$g_b = \in \{p_0(t), p_1(t), p_2(t) \dots\dots\dots\dots\dots\dots\dots p_m(t)\} = \min \{f_n(p_0(t)), f_n(p_1(t)) \dots\dots\dots\dots\dots\dots\dots f_n(p_m(t))\} \quad (2)$$

The particle velocity and position is computed and upgraded using the following equations 3 and 4,

$$v_i(t+1) = w_i v_i(t) + q_1 a_1 (p_i(t) - c_i(t)) + q_2 a_2 (p_i(t) g_b - c_i(t)) \quad (3)$$

$$c_i(t+1) = c_i(t) + v_i(t+1) \quad (4)$$

where w_i specifies interim weight [25], q_1 and q_2 are constants, a_1 and $a_2 \in [0,1]$ which are random numbers, v_i is the particle velocity with the constraint of the specified range of minimum value to maximum value$[v_m, v_x]$, if $v_i > v_x$ then $v_i = v_x$ and if $v_i < v_m$ then $v_i = v_m$.

B. Darwinian Particle Swarm Optimization (DPSO)

DPSO is an extension of cnventional PSO which was articulated by Tillet et al [26] in exploring a model for natural selection using a well-known PSO. DPSO addresses the problem of local minima where numerous test solutions of swarm may present at any moment. The swarm which performs independently better in the PSO algorithm, by satisfying the constraints respect to collection of swarms which are designated for natural selection simulation. DPSO runs many PSO algorithms concurrently for a different swarm using same test problem. Swarm which shows better behavior are saved for generating further descendants and the swarm which does not perform better are deleted. Fitness of the particles is assessed by upgrading its position and new particle is generated if it finds global optimal solution. Particle elimination is carried out if the swarm is not able to find its state in predefined steps or it falls below the lower bound. The procedure for deleting a swarm is described in Figure 2.

Main Program loop
For each swarm in the collection
Evolve the swarm (evolve swarm algorithm: right)
Allow the swarm to spawn
delete "failed" swarm

Evolve swarm algorithm
For each particles in the swarm
Update particles fitness
Updates particles Best
Move Particle
If the swarm gets better
Reward swarm: swarm particle:
Extend swarm life
If swarm has not improved
Punish swarm:possible delete
Particle:reduce swarm life

Figure 2: Algorithm for DPSO

After eliminating a particle, the swarm is reset to the value reaching the threshold based on the equation 5.

$$PC_c N_{del} = PC_c^{max}\left[1 - \frac{1}{N_{del}+1}\right] \quad (5)$$

Where N_{kill} is the particles deleted from the swarm which does not gain the fitness over a period of time. To create a new swarm, the particle should not have been eliminated from the swarm and not exceeding the specified limit for the swarm.

C. Fractional Order – DPSO (FO-DPSO)

DPSO is further reconstructed using fractional calculus to administer the rate of convergence in conventional PSO. The advantage of fractional calculus is utilized by researchers which have widespread applications sprawling in several fields including engineering, mathematics, mechanics etc. Analogous to traditional PSO, in FO-DPSO [27][28] the particles glide through a specified search and socialize with the other particles by sharing the information. In every step the efficiency of the particle is assessed by its fitness function [29]. The particles and velocity is updated fractionally using individual and global best position using the following formulation 6 and 7.

$$v_i(t+1) = w_i v_i(t) + \frac{1}{2} w_i v_i(t-1) + \frac{1}{6} w_i (1-w_i) v_i(t-2) + \frac{1}{24} w_i (1-w_i)(2-w_i) v_i(t-3) + q_1 a_1 \big(p_i(t) - c_i(t)\big) + q_2 a_2 \left(p_i(t) g_b - c_i(t)\right) \quad (6)$$

$$c_i(t+1) = c_i(t) + v_i(t+1) \quad (7)$$

The inertial influence is controlled by the fractional coefficients of the particles. The fractional coefficient will impact in finding new velocity [0, 1] considering past events. Initially, particle's velocity is assigned with zero and search space is set within the boundaries when computing thresholding of FODPSO of images. Further, every particle in the swarm is compared with every other particle for a possible solution in the solution space. The larger between-class variance of the particle is considered as best performing particle which attracts other particles to it. Particles higher exploitation behavior is noted when it can find maximum between-class from one step to another which leads to cumulative convergence of the algorithm.
Further, ten similarity metrics are employed to evaluate the uniformity of the segmented image. Table 1 describes the similarity metrics used to assess the results obtained.

Table 1: Similarity Metrics

S. No	Similarity Index	Formula
1	Anderberg	$\frac{(t1 - t2)}{(2 * m + n + o + p)}$ $t1 = \max(m,n) + \max(o,p) + \max(m,o) + \max(n,p)$ $t2 = \max((m+o),(n+p)) + \max((m+p),(o+p))$
2	Braun and Blanquet	$\frac{m}{\max((m+n),(m+o))}$
3	Dice	$\frac{(2 * m)}{((2 * m) + n + o)}$
4	Dice Asymmetric I	$\frac{m}{(m+o)}$
5	Dice Asymmetric II	$\frac{m}{(m+n)}$
6	Hawkin's and Dotson	$0.5 * \left(\left(\frac{m}{(m+n+o)}\right) + \left(\frac{p}{(n+o+p)}\right)\right)$
7	Jaccard	$\frac{m}{(m+n+o)}$
8	Simple Matching	$\frac{(m+p)}{(m+n+o+p)}$
9	Sokal and Sneath I	$\frac{(2 * (m+p))}{((2 * (m+p)) + n + o)};$
10	Sokal and Sneath IV	$\left(\frac{((m/(m+n)) + (m/(m+o))) + (p/(n+p)) + (p/(o+p))}{4}\right)$

Let $G_{i,j}$ be the ground truth and $S_{i,j}$ be the segmented image then variable mentioned in the similarity measure is the count of the ground truth $G_{i,j}$ and segmented image $S_{i,j}$ has the value 1. Number of times the ground truth $G_{i,j}$ has the value 0 and segmented image $S_{i,j}$ has the value 1 is represented using the variable b. Similarly variable c denotes the number of times ground truth $G_{i,j}$ has the value 1 and segmented image $S_{i,j}$ has the value 0.

The variable m denotes the pixels in numbers with positive matches, n denotes the number of pixels of absence mismatches in ground truth $G_{i,j}$, o denotes the enumeration of pixels of absence mismatches in segmented image $S_{i,j}$ and p denotes the total count of negative matches in pixels. The total value of matches in $G_{i,j}$ and $S_{i,j}$ are quantifies in the diagonal m+p. Similarly, number of mismatches in diagonal is represented at n+o. The total quantity of pixels in the image is equal to sum of the table m+n+o+p [30]. The evaluation of the uniformity of similarity between segmented and ground truth is also depicted in dendogram plot. The plot manifests the cluster formations of similarity measures between the data which is dependent.

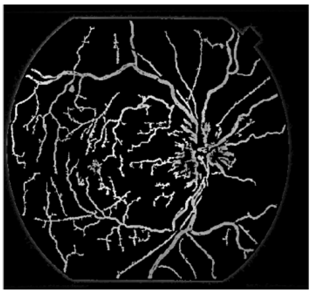
III. RESULTS

In this research, retinal digital color fundus images are obtained from STARE project with experts hand labeled ground truth. The retinal images are acquired using fundus color optical camera from the internal surface of the eye ball in pupil. Segmented image obtained depicts the retinal nerve, optical nerve, surrounding blood vessels and the fovea. After acquiring the image experts had label the image with the observed findings. Images of different size obtained are resized to same size of [512 x 512]. The resized images are subjected to CLAHE to improve contrast and filtered using average filter for eliminating noise present in the image. Further, PSO, DPSO and FO-DPSO techniques are imposed for segmenting the blood vessels from the image.

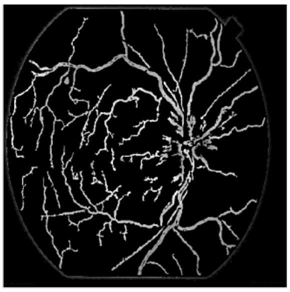
Results of the retinal vasculature of the digital fundus image obtained using PSO, DPSO and FO-DPSO is shown in figure 3(a) – 3(e).

Representative images and their segmented images along with ground truth are shown in the figures 3(a)-3(e). The pre-processed images are segmented using PSO, DPSO and FO-DPSO is shown in figure 3(b)-3(d). The segmented retinal vasculature clearly reveals the visual quality of the segmentation process. Application of swarm intelligence techniques in digital fundus retinal image manifests that FO-DPSO performs better than PSO and DPSO which is evident from the results obtained. This evident is also supported by the similarity values computed between the ground truth and the segmented images which are described using box and dendogram plot.

3(a)

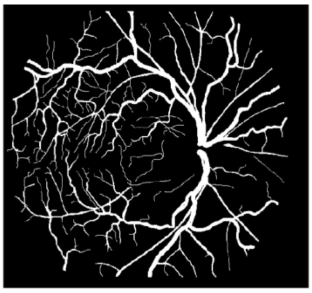


3(b)



3(c)

3(d)



3(e)

Figure 3(a) : Retinal Digital Fundus Image ; 3(b) Segmented image using PSO; 3(c) Segmented image using DPSO; 3(d) Segmented image using FO-PSO; 3(e) Ground Truth

Figure 4,5 and 6 shows the box plot of the retinal vasculature obtained in contrast with ground truth using PSO, DPSO and FO-DPSO respectively.

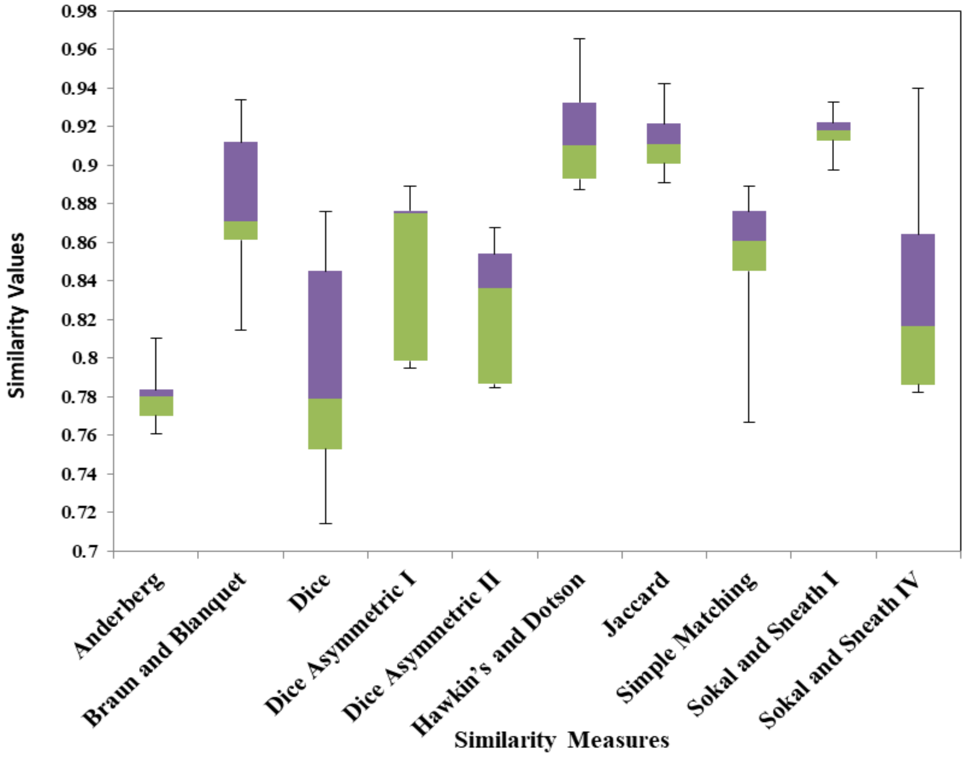


Figure 4: Box plot for Similarity Measures – PSO

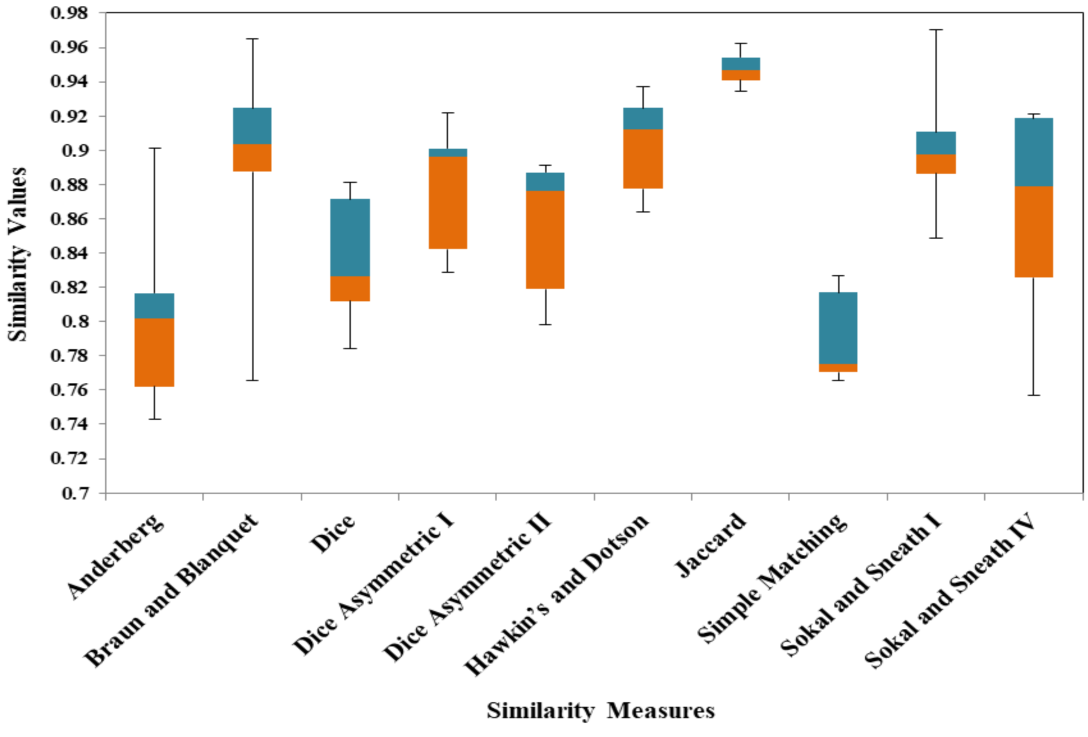


Figure 5: Box plot for Similarity Measures – DPSO

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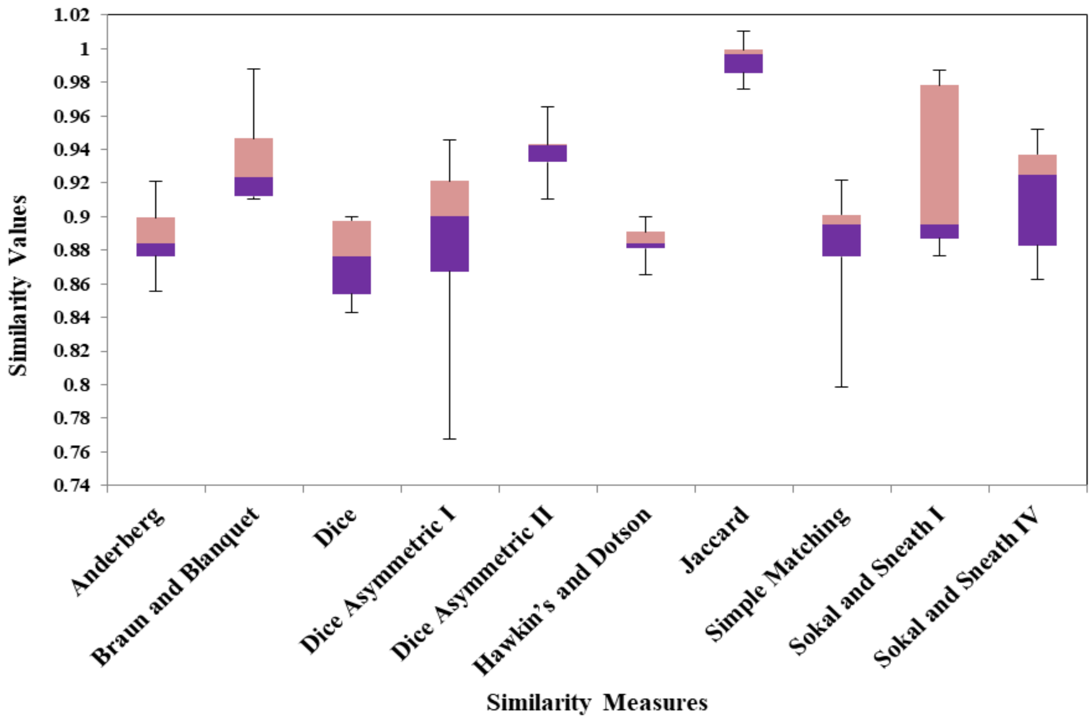

Figure 6: Box plot for Similarity Measures – FO-DPSO

The closeness of the similarity measures for the images is shown in Figure 7, 8 and 9 for PSO, DPSO and FO-DPSO respectively. The hierarchical clustering of closeness in similarity measures is shown using dendogram. Euclidean distance is applied to measure the closeness of the measures. Results reveal that PSO has exhibited three clusters with the closeness maximum value of 0.40 and DPSO has shown a closeness value of 0.38 with 4 clusters. Similarly FO-DPSO has the closeness value 0f 0.30 with 4 clusters. The results clearly manifests that FO-DPSO has shown better performance in segmenting the retinal image than PSO and DPSO.

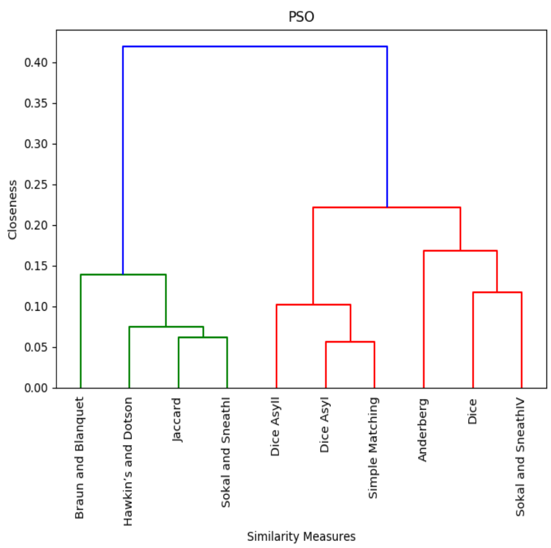

Figure 7: Dendogram plot for PSO

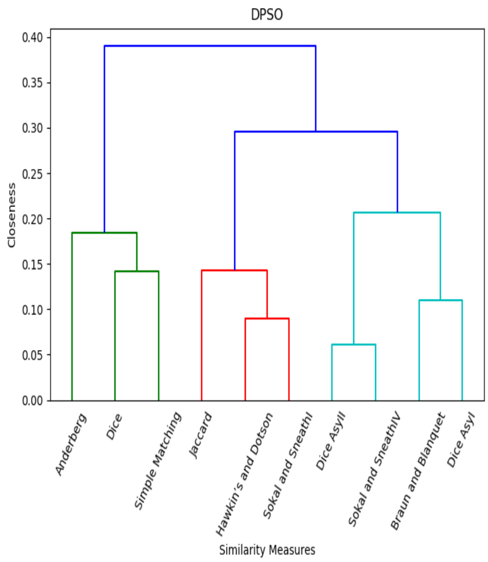

Figure 8: Dendogram plot for DPSO

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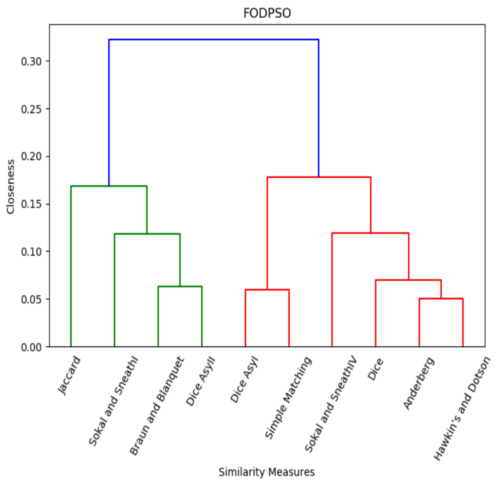

Figure 9: Dendogram plot for FO-DPSO

IV. CONCLUSION

In this work, swarm intelligence techniques PSO, DPSO and FO-DPSO were utilized in segmenting the retinal blood vessels. CLAHE and Average filter are used for pre-processing have onsiderably enhanced image which assists in better segmentation. The use of similarity measures aids in evaluating and validating the swarm intelligence technique with ground truth. From the boxplot and dendogram, it is evident that swarm intelligence techniques segments blood vessels with significantly higher accuracy. Specifically, FO-DPSO has shown higher similarity indices when compared to PSO and DPSO. From the results, it is observed that jaccard similarity has exhibited higher mean values of (0.91326,0.94764,0.99148) for PSO, DPSO and FO-DPSO. Next to jaccard, Sokal and Sneath I (0.91656, 0.90278,0.9249), Braun and Blanquat (0.878616, 0.88912, 0.9362) have revealed the higher mean values. This is also evident in dendogram for PSO and FO-DPSO the similarity measures are in the same clusters. Results clearly indicate that FO-DPSO has segmented better in contrast to PSO and DPSO.

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AUTHORS PROFILE

Dr. A. Anitha, currently working as an Assistant Professor in PG Department of Computer Science at D.G Vaishnav College, Chennai having teaching experience of 15 years. **She** had pursued her doctoral degree in Bharathiar university, Coimbatore and her research interests includes Data Mining, Bio-Medical Engineering, Image Processing and Cryptography.

Dr. T. Sridevi, currently working as an Assistant Professor in PG and Research Department of Computer Applications, D.G. Vaishnav College, Chennai, having 20 years of teaching experience. She had obtained her doctoral degree in Mother Terasa Womens University, Kodaikanal. Her research interests are Data Mining, Internet of Things and Image Processing.