

An Efficient Vessel Segmentation Based on Hierarchical Swarm Optimization Scheme and Mean Shift Clustering with Vessel Connectivities for Retinal Images

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Key words: Retinal blood vessel, segmentation, clustering, vessel connectivity, HCSO, Boltzmann equation

Abstract: Retinal images provide early signs of diabetic retinopathy, glaucoma and hypertension. These signs can be investigated based on micro aneurysms or smaller vessels. These studies require accurate tracing of retinal vessel structure from fundus images in an automated manner. However, the existing threshold based segmentation encounters great difficulties such as the detected edges are consisted of discrete pixels and may be incomplete or discontinuous and computationally expensive. To solve above problem, Hierarchical Cat Swarm behaviour based Optimization scheme (HCSO) with Mean Shift Clustering (MSC) algorithm is proposed in this study. In diagnosis, the vessel angles and lengths are changed particularly in junctions and it's detected by using vessel segmentation. Also the bifurcations and crossings are disconnected and the vessel paths are interrupted in retinal image. So, the proposed system focused these kinds of junction problems. Initially, the input image is pre-processed using top hat filtering to enhance the accurate vessel extraction. Then, the geometric structure based features are extracted by using morphological scheme. Here, the junction problem is analyzed through a connectivity kernel. The experimental result shows the proposed work has efficient and effective vessel segmentation and can be useful for image-aided diagnosis systems and further applications.

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INTRODUCTION

Now a days, the analyses of eye fundus images are very important for diagnosing the many eye diseases like diabetic retinopathy, glaucoma and macular degeneration (Lee *et al.*, 2001; Tasman *et al.*, 2006). If these diseases are not detected in right time it causes the blindness of people. So, to detect and diagnosis of many eye diseases, the retinal blood vessel segmentation scheme has been introduced. The vessel blood vessels extract information's like branching patterns and tortuosity. It's not only provided pathological changes information and also help to status the disease severity as well as automatically diagnoses the disease. Though retinal vessel segmentation has been studied widely but still it is a challenging problem due to three main reasons. At first, the quality of

image is not good variable and high homogeneity of illumination or low contrast (Setiawan *et al.*, 2013; Imani *et al.*, 2015) in segmentation methods. Second, most of the existing schemes find it was very difficult to identify the complexity of vascular structures like different scales and orientations with linear orientations (Zhao *et al.*, 2015; Lathen *et al.*, 2010; Miri and Mahloojifar, 2011; Fraz *et al.*, 2012a, b Bankhead *et al.*, 2012; Wang *et al.*, 2013; Liao *et al.*, 2014). Finally, to find the optimum model for variety of data is very difficult (Hoover *et al.*, 2000; Kauppi Tomi *et al.*, 2017; Niemeijer *et al.*, 2010). Earlier, various schemes are focused for segmentation and it classified into pattern recognition using machine learning or model-based (Imani *et al.*, 2015; Niemeijer *et al.*, 2010; Marin *et al.*, 2011) mathematical morphology (Imani *et al.*, 2015;

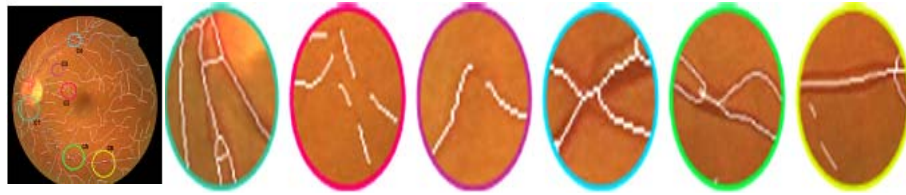


Fig. 1: A sample image for vessel selection from the DRIVE dataset

Mithun *et al.*, 2014), kernel-based analysis (Bankhead *et al.*, 2012; Wang *et al.*, 2013; Fraz *et al.*, 2012a, b) and tracking-based or path-based Artificial Intelligent (AI) methods (Zhao *et al.*, 2015; Estrada *et al.*, 2012; Yin *et al.*, 2012). Here, kernel based analysis with threshold based segmentation has been discussed because they are more related to presented work.

The retinal vessels are connected in the form of tree structure. The intensity of vessels and local orientation is change slowly along their lengths. Though, these local properties were varied highly for different vessels. Earlier studies show that the morphological quantitative measurement and geometrical attributes of retinal vasculature like tortuosity, vessel diameter, branching pattern, arteriovenous ratio and angles are very informative in early diagnosis and prediction of various diseases (Chapman *et al.*, 2002; Habib *et al.*, 2014; Lowell *et al.*, 2004; Smith *et al.*, 2004). Particularly, as two blood vessels along with the same type never cross each other is very difficult for detecting original blood vessel. So, the behaviour of blood vessels at crossings has been mainly focused to diagnosis the diseases. Various difficulties are there for both vessel tracking and vessel segmentation. Generally, these retinal images could be affected through noise in various degrees depending on imaging technology and conditions. Particularly, the drift in image intensity, non-uniform luminosity, central vessel reflex and low contrast regions are making the complication for vessel segmentation, detection and tracking methods. To solve the above problem, various schemes like image enhancement, denoising and normalization has been introduced (Abbasi-Sureshjani *et al.*, 2015; Azzopardi *et al.*, 2015; Foracchia *et al.*, 2005; Narasimha-Iyer *et al.*, 2008). The segmentation is used to splitting the vessels like disease affected vessel and not affected vessel for efficient diagnosis. For that, the vessel tracking has been introduced to extract and identify the vessels in crossing sections. The tracking is exploiting the skeleton of the segmented retinal images. Therefore, various methods have been proposed (Al-Diri *et al.*, 2009; De *et al.*, 2013, 2014; Gonzalez *et al.*, 2010; Joshi *et al.*, 2011) to solve the non-perfect segmentation problem or wrong skeleton extraction. Because, these results are tracing the error in topological structure like non-complete sub trees and disconnections. The non-complete sub trees includes wrongly merged parallel vessels, missing small vessels,

the occurrence of spur branches in thinning and broken up vessel segments. In addition, the main difficulty is arising in crossovers and junction. Some of these difficulties are showed in Fig. 1. It illustrates the difficulties like complex junctions when some junctions are close together and small arteriovenous crossing angles. To solve these difficulties, various schemes have been proposed in earlier. Mainly, to find the connectivity problem, the segmentation and tracking based approaches used in a vessel profile. The main benefit of this scheme is it provides exact vessel width, unlike other schemes. There are many studies are following this scheme like graph-cut (Zhao *et al.*, 2015), Bayesian-based tracking (Yin *et al.*, 2012), dijkstra shortest path for vessel patterns (Estrada *et al.*, 2012) and graph-analysis (Dashtbozorg *et al.*, 2014).

Figure 1 illustrates the various difficult cases of vessels like C1-C5 and C6. C1 indicates the complex junction with the presence of a bifurcation and a crossing with a narrow crossing angle, C2 represents interrupted lines and missing small vessels, C3 shows high curvature vessel, C4 defines a crossing and bifurcation, complex junction, wrong thinning at crossing, C5 represents two nearby parallel vessels merged as one group and C6 shows merged parallel vessels, missing small vessel and interrupted segment. In this study, an efficient HCSO with MSC algorithm is proposed for extracting the vessels from retinal image to diagnosis eye diseases. For improve the vessel segmentation accuracy, the input image is pre-processed using top hat filtering. To reduce the computational time, the features are extracted efficiently using morphological approach. This scheme has been mainly based on arteriovenous crossings like intensity of the artery, continuity in orientation and like intensity of the vein that is the intensity of individual vessels and local variation of orientation is very low. In this proposed scheme, the Boltzmann equation based connectivity carried and it matches the statistical distribution of edge co-occurrence in natural images. It's also good model of the cortical connectivity. Finally, the vessels are segmented using HCSO. In HCSO, all particles are arranged in a regular tree structure and move up or down in the tree based on their fitness value and MSC used similar principle with smoothing to improve the segmentation efficiency. The experimental result shows the proposed scheme attained high segmentation result compared than existing schemes.

Literature review: In this study, various types of existing algorithms were deployed for vessels segmentation has been discussed. By Jusoh *et al.* (2016) surveyed a retinal vessel segmentation schemes. Here, the segmentation schemes were studied and analysed based on the DRIVE and STARE datasets. The segmentation was mainly used for detecting the retinal abnormalities. The supervised and unsupervised are presented in this survey and their results also evaluated by using these two datasets. It results show that the supervised scheme attained better segmentation results but it needs training images. Taking the training images was little difficult. Consequently, the unsupervised results attained faster performance and it do not need any training image. But the segmentation perdition accuracy was less. This survey provided idea for future research to develop a fast and efficient algorithm for achieving a high level of accuracy. Dasgupta and Singh (2017) presented a Convolutional Neural Networks (CNN) based segmentation scheme for retinal blood vessel segmentation and structured prediction. It also learns hierarchical features from raw pixel data with no knowledge of domain. These features are very tedious. This scheme performance was evaluated by DRIVE dataset and the simulation results show that the CNN achieved good performance and extensively outperforms compared than existing schemes for automatic retinal vessel segmentation with accuracy of 95.33% value and AUC score of 0.974 value. The CNN can only processed the large dataset, so, the computational time was attained high.

Kumar *et al.* (2014) presented a centreline tracing based scheme for concurrent blood vessel segmentation and estimate the radius. This scheme has two analyses like trunk and bifurcation. At first, the trunk analysis was carried out. In this analysis, the vessels are segmented by using 2D cross-section analysis. Second, the vessel was segmented by using modified vesselness in bifurcation analysis. The performance of this scheme was evaluated for angiogram images. The experimental results show that this scheme 20 times faster than existing schemes for finding the blood vessel centreline. It also attained good accuracy with less mean error. But it's not focused discontinuities at bifurcations, so the performance was decreased.

Kuri and Kulkarni (2015) proposed a filter based segmentation for acquiring blood vessels with high accuracy. This scheme was composed of an Improved Gabor Filter (IGF) with Regional Entropy Thresholding (RET) based on certain normal and abnormal situations. To fit an integral part of blood vessels, the volume and alignment of gabor filter was updated which increased in the green component of the image. The performance was evaluated for DRIVE dataset. The experimental results show that this scheme attained average accuracy of

97.94% and sensitivity of 98.5%. The accuracy was improved by noise reduction scheme. But the system was not robust. Roychowdhury *et al.* (2015) developed a Gaussian Mixture Model (GMM) classifier based segmentation scheme for retinal blood vessel segmentation. This scheme has three stage of process like pre-processing, vessel extraction and segmentation. At first, high-pass filtering scheme used for noise reduction and then the binary image was extracted. After that, the binary image was reconstructed from morphologically to enhance the image for efficient vessel regions. From these two images, the common regions of major vessel was extracted and then GMM was used for classify all pixels from two binary images. In GMM, 8 features are used which are extracted from pixel neighbourhood and first and second order gradient images. Finally, the image vessels and classified vessels are combined. This scheme performance was evaluated for DRIVE. The simulation results show that the scheme achieved the high accuracy of 95.2%. But it has computational complexity.

Hou (2014) presented an automated enhancement segmentation based on multi-scale line detector for retinal blood vessel images. Initially, the Optic Disc (OD) was vessels are emphasized by using Morphological Multidirectional Top-Hat Transform (MM-THT). The structuring elements are considered for background of the retinal image rotation. Then to generate a vessel response image an Improved Multi-Scale Line Detector (IMSLD) was used and formed the last blood vessel tree. It has various detectors like long and small. For different scales, the weight values are set as different values, all the responses are merged through the IMSLD at different scales. The performance of this scheme was evaluated for DRIVE and the results attained accuracy of 0.942, sensitivity of 0.735 and specificity of 0.969. But it suffers from computational complexity.

Yin *et al.* (2013) presented a probabilistic tracking-based segmentation scheme for automatic retinal blood vessel segmentation. At first, the vessel edge has been detected for whole image and also handles carious vessel structures. In tracking process, to detect the edge points the Bayesian method with Maximum a Posteriori (BMP) has been carried out. This scheme performance was evaluated for three publically available dataset like STARE, DRIVE and REVIEW. The simulations results of this scheme achieved specificity and sensitivity on STARE was 0.9666 and 0.7248 as well as sensitivity of 0.6522 and specificity of 0.9710 on drive. The performance accuracy was not good.

Fraz *et al.* (2012a, b) proposed vessel centrelines based segmentation scheme with morphological bit plane slicing. Initially, gaussian filter was used for extracting the centrelines and then processing an average derivative and derivative signs with the extracted centrelines. After

that, the morphological multidirectional top-hat operation was processed in gray scale retinal vessel image with linear structure element to attain shape orientation map and then passed to the bit plane slicing. To obtain vessel tree, the maps are combined with centrelines. This scheme performance was evaluated for three publically available dataset like STARE, DRIVE and MESSIDOR. The simulations results of this scheme achieved accuracy on DRIVE 0.94 and accuracy on STARE of 0.941 and MSSIDOR 0.958. It has computational complexity.

Sun *et al.* (2011) presented a morphological multi scale enhancement scheme for blood vessel extraction in the angiogram by using watershed transformation and fuzzy filter. To, estimate the background, multi-scale morphology opening operators was introduced. After that, contrast normalization was attained and integrated with fuzzy morphological operation. It was applied on the angiogram with 12 linear structuring elements and 9 pixels length. to obtain the vessel region, thres holding the filtered image and then thinning operation was applied for approximating the vessels centrelines. Finally, to detect the vessel boundaries the watershed scheme was applied on vessel centreline.

The simulations results of this scheme achieved accuracy, specificity and sensitivity on DRIVE database 0.943, 0.715, 0.977. But the system was not robust and stability also not good.

MATERIALS AND METHODS

In this study, the proposed HCSO with MSC based retinal blood vessel segmentation has been discussed. It contains three stages such as pre-processing, effectual feature extraction and efficient segmentation. These stages are explained in given below subsections.

The overall architecture of proposed scheme is illustrated in Fig. 2. It shows the step by step segmentation process of proposed scheme. Initially, the input image is pre-processed. Subsequently, the features are extracted for vessel segmentation. A hierarchical algorithm has been carried out for segmentation. In this hierarchical scheme, first MFC scheme is processed to get pre-segment affinity matrix. After that, the CSO algorithm is introduced to find the fitness value to separate the vessel and non-vessel structures. Finally, the vessels are tracked by using HCSO. The extracted vessel intensities or types represented as various color segmentation in simulation results. The experimental results show that the proposed scheme attained better performance and high accuracy compared than existing algorithms.

Pre-processing using top-hat filtering: In this system, the pre-processing has two steps for efficient feature

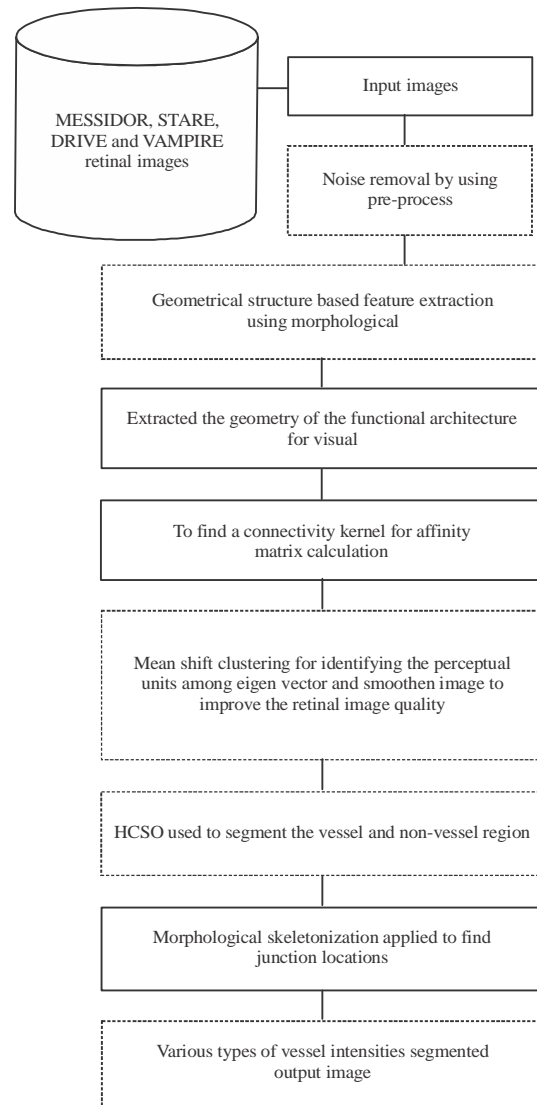


Fig. 2: Overall process of proposed HCSO with MHC segmentation

extraction and it shows a high contrast among vessel and non-vessel objects make easy the segmentation process. In first step, the effect of background variations is removed by using non-uniform illumination. In second step, the complexity of vascular structure and noise are removed by top-hat filtering scheme. In this pre-processing, the green channel image is choosing for process because it exhibits the best vessel and non-vessel contrast in retinal images. Also, it can be decreased the computational time compared to all RGB processing channels. First, the Region of Interest (ROI) features are extracted and it represents a circle like nonblack region or shape at the center of retinal images. To find efficient ROI, minimum threshold value has been

used for all RGB images to eliminate surplus background from RGB channel and it can be improve the ROI performance. Though, some missed labeled pixels are produced on retinal background and foreground. These noises are eliminated by morphological operations like Top Hat Filtering (THF).

The THF operation is executed based on shapes in retinal images and it is formed via. structuring element. In this process, the matrix containing 0's and 1's where neighbourhood pixels are denoted as 1's. These processing pixel neighbours are used to determine the output pixel. It has two operations like dilation and erosions. These operations are performed in retinal image with disk structuring element for reducing the noise and efficient feature extraction. At first, the pixels are adding in object boundary based on structuring element is called as dilation and the rule to discover output pixel and is denoted as the maximum of input pixels neighbourhood matrix. Second, erosion is used to delete the pixel from the object boundary based on structuring element. The rule is used to discover output pixel. By using the dilation and erosion, the morphological opening and closing operations are carried out. The opened and closed images are subtracted to reduce the noise from image. Finally, the for edge sharpness and reducing distortion from background, the image is smoothed. It is done by top hat transform opening and closing operation and defined as:

$$(I \circ S) = \text{Dilation} (\text{Erosion}(I, S), S) \quad (1)$$

$$(I \bullet S) = \text{Erosion} (\text{Dilation}(I, S), S) \quad (2)$$

Where:

I : The structuring element is defined

S : The opening operation denoted

◦ : Denotes the closing operation denoted as

Feature extraction using morphological operator: The feature extraction used for efficient segmentation. The retinal vessel image feature extracted by using mathematical morphology. It is a nonlinear method and is used the concepts of topology, set and geometry. The geometry used to analyse the geometrical structures like shape and form objects in images. It observes the geometric structure of an image via. searching with structuring elements. In this research, the features are extracted by using black Top-Hat Transform (THT) morphological operator.

This operator is used to extract image structure with lower illumination conditions (Soille, 2013). This operation carried out by subtracting morphological closing image $\phi(c(x))$ of corrected image from corrected

image $c(x)$. The morphological closing $\phi(c)$ is defined as the process of dilation $\alpha_B(c)$ followed by erosion $\beta_B(c)$ and then acts as a shape filter to defends objects having relevant structure and is given as:

$$\text{Block THT}(c) = \phi(c(x)-c(x)) \quad (3)$$

$$\phi(c) = \beta_B(c)(\alpha_B(c)) \quad (4)$$

The exact structure of image has been extracted from this step. After that, the geometry structure of the visual cortex is extracted by using cake wavelet for exact region segmentation.

Extraction of visual cortex using cake wavelet: The visual cortex is arranged in a hyper columnar structure and is denoted as where each point corresponds to a simple cell and this cell extract the orientation information at all locations (p, q) and send a send a multi-orientation field. Based on this concept a new transformation of cake wavelet is introduced to avoid loss of information. The cake wavelet is similar to Gabor wavelet functions and has a high response on oriented and extended structures. For the motivation of constructing the higher dimension representation, $U_c:SE(2) \rightarrow C$, the input image $c(p,q)$ is correlated with the anisotropic cake wavelet ψ (Duits *et al.*, 2007a, b Franken and Duits, 2009; Sanguinetti *et al.*, 2010):

$$U_c(p, \vartheta) = (w_\psi[c])(p, \vartheta) = (\sqrt{R_\vartheta}(\psi) * C)(p) = \int_{R^2} \overline{\psi(R_\vartheta^{-1}(q-p))} c(q) dq \quad (5)$$

where, R_ϑ is defined as the 2 D counter-clockwise rotation matrix R_ϑ , ϑ is represented the orientations R^2 represented as space of positions. Then, this transformation is considered for only one orientation (i.e., highest transformation response) preposition, the points of a curve $\Gamma = (p, q)$ are lifted to new cortical curves and is defined in the space (p, q, ϑ):

$$(p, q) \rightarrow (p, q, \vartheta)$$

These curves have been modelled as integral curves of suitable vector fields and defined as:

$$P_1 = (\cos \vartheta, \sin \vartheta, 0), P_2 = (0, 0, 1) \quad (6)$$

The lifted curves two pints are connected via. integral curves of these two vector fields such that:

$$\begin{aligned} \Gamma: \mathbb{R} &\rightarrow \text{SE}(2), \Gamma(s) = (p(s), q(s), \vartheta(s)) \\ \Gamma'(s) &= (k_1(s)P_1 + k_2(s)P_2)(\Gamma(s)), \Gamma(0) = 0 \end{aligned} \quad (7)$$

where, the coefficients k_1 and k_2 represent a distance in the (p, q, ϑ) domain, s is defined as joint space of orientation. These curves projected on the 2D cortical plane to signify a better model of the association fields. To include the intensity term of Euclidean distance among the intensities of two corresponding points. It signifies the image intensity at position the stimulus and is lifted to the extended 4-dimensional feature space and is defined as:

$$(p, q, \vartheta) \rightarrow (p, q, \vartheta, c(p, q))$$

Starting from these vector fields the proposed system can model the cortical connectivity.

Model of cortical connectivity kernels: The probability of connecting two points in the cortex defined as the cortical connectivity and is signified via. stochastic counterpart of the curves in Eq. 7 is given as:

$$(p', q', \vartheta') = P_1 + N(0, \sigma^2)P_2 \quad (8)$$

where, $N(0, \sigma^2)$ is represented as a normally distributed variable with mean value of zero and variance of σ^2 . In this proposed scheme, the probability density v can be used to find a particle at the point (p, q) and it started from a given location (x', y') which moving with some known velocity. Then, the v satisfies a deterministic equation known as boltzmann equation is given as:

$$\partial_t v = P_1 v + \sigma^2 \partial_{\vartheta\vartheta} v$$

Where:

P_1 : Defined as the directional derivative $\cos(\vartheta) \partial_p \sin(\vartheta)$
 ∂_q and $\partial_{\vartheta\vartheta}$: Denoted as the second-order derivative

The Boltzmann fundamental solution to obtain connectivity kernel ω_1 by symmetrisation is:

$$\omega_1((p, q, \vartheta), (p', q', \vartheta')) + Y_1((p', q', \vartheta'), (p, q, \vartheta))$$

where, γ_1 is defined as nonnegative fundamental solution. With the intention of measure the distances among intensities the proposed system introduces another kernel $\omega_2((p_i, q_i), (p_j, q_j))$ and the new intensity kernel can be defined as:

$$\omega_1(c_i, c_j) = e^{\left(\frac{1}{2} \left(\frac{c_i - c_j}{\sigma^2}\right)^2\right)} \quad (9)$$

Based on the product of the two components, the final connectivity kernel can be written as:

$$\begin{aligned} \omega_c &= \left((p_i, q_i, \vartheta_i, c_i), (p_j, q_j, \vartheta_j, c_j) \right) = \\ &\omega_1((p_i, q_i, \vartheta_i), (p_j, q_j, \vartheta_j)) \omega_2(c_i, c_j) \end{aligned}$$

Based on this kernel the affinity matrix can be predicted for to separate the disease affected vessel and non-affected vessel.

Calculation of affinity matrix: The connectivity kernel is used to extract perceptual units from retinal images by mean shift analysis of suitable affinity matrices. In this process, the highest eigen value of eigenvectors are linked to the most salient objects in the scene and the connectivity is signified through a real symmetric matrix $AF_{i,j}$ is:

$$AF_{i,j} = \omega_c \left((p_i, q_i, \vartheta_i, c_i), (p_j, q_j, \vartheta_j, c_j) \right) \quad (10)$$

This matrix contains information of connectivity among all the lifted points and eigenvectors of the affinity matrix taken as perceptual units (Sanguinetti *et al.*, 2010).

Mean Shift Clustering (MSC) algorithm: Based on the eigen values the clustering has been carried out. The aid of MSC is separate the eigen values into several groups like similar values of data is grouped into same group and dissimilar value of data can be grouped in to another group. Because to identify the disease affected and non-affected vessels. In order to perform visual grouping, the proposed system used the MSC algorithm. In this process, first the smoothing process is carried due to the segmentation can be observed as extension of smoothing. It's required to process simultaneously image's spatial location information and color information for the processing of color images. So, inputting any pixel of the image is described as one 5D information vector in the expression $= (x^s, x^r)$ where x^s is defined as 2D spatial location coordinate, x^r is defined as 3D color feature vector. The kernel function is expressed as follows:

$$K_{r_k \dots r_s} = \frac{N_c}{r_k^d r_s^d} w_c \left(\left\| \frac{x^k}{r_k} \right\|^2 \right) w_c \left(\left\| \frac{x^{fs}}{r_s} \right\|^2 \right) \quad (11)$$

Where:

N_c : A normalized constant

ρ and d : Space dimension ($\rho = 3, d = 2$)

r_k : Radius of the kernel function, indicative of space's kernel size

r_{fs} : Radius of feature space, the kernel size of value range
 w_c : Affinity matrix

$$P_i = \frac{|SE_i - SE_{max}|}{SE_{max} - SE_{min}}, 0 < i < j \quad (12)$$

In input image, clustering all pixels are converged via. one maximum value point of the same density and assigning cluster's label to all points in the cluster. Then, the optimized threshold based retinal blood vessel segmented by using HCSO algorithm.

Hierarchical cat swarm optimization: In this study, the HCSO process has been proposed for efficient segmentation. In the proposed HCSO scheme, all particles are organized in a regular tree structure and travel up or down in the tree based on their fitness value. It depends on the position and velocity of each particle in the tree for the velocity update of each particle. Besides, a mutation operator is added into the proposed HCSO approach. Consequently, the diversity of the population increases in order that the HCSO approach can recover the premature convergence in the CSO approach.

In the HCSO, all particles are arranged in a hierarchy that defines a regular tree structure. The structure of the regular tree is determined by the height (h) and the branching degree (d) of the tree, so that, m nodes.

Step 1; Initialize the HCSO: Set the height of the tree (h), the branching degree of the tree (d), the maximum number of iterations (G), the constants for the HCSO (c_1 , c_2 , w, r) and the mutation rate (P_m). Randomly generated the initial population P in the nodes of the tree. The individual population performance is defined as follows. Here, the population is mentioned as the cat, it has own Velocity (Ve) and Position (Po) and the fitness value represent the accommodation of the cat. It also has two mode of processing like seeking and tracing mode and is represented as Flag (F) Function.

Step 2; Seeking mode: Cat in rest time and is altered as known as seeking. Here, checked the attained threshold values are higher than the predefined value is processed in this mode. In this mode, 4 parameters are considered like range of selected Po, memory pool, number of position to change and consideration of self-position. The process is given as. Set I = memory pool of the present cat (i.e., pixel) position. Check if the consideration of self-position is true and then set I = (memory pool-1) after that keep the present position of cat. Randomly the plus or minus values are presented for each copy with number of position to change and range of selected Po. Fitness value (Ftv) for all pixel is calculated. Check if all fitness value equal, all the probability of each pixel set as 1. Otherwise selecting probability computed for all pixel point by using given (Eq. 12):

where, SE is a defined as Sum of squared-Error. If the aid of the fitness value find minimum solution $Ftv = Ftv_{max}$ otherwise $Ftv = Ftv_{min}$. Randomly to get the point from candidate point and update the position of cat (i.e., pixel).

Step 3; Tracing mode: It is mainly used for find the exact fitness to separate the disease affected region and to segment the exact part. Initially, the velocities of every position has been updated using given (Eq. 13):

$$Ve_{c,d} = Ve_{c,d} + r_1 c_1 (x_{bset,d} - X_{c,d}) \quad (13)$$

Where:

- $x_{bset,d}$: The position of the cat which has best fitness value
- $X_{k,d}$: The position of cat c
- c, c_1 : Acceleration coefficient
- r_1 : Randomly generated value range [0,1]

Check if the Velocity (Ve) maximum or not. If maximum means it is update and replace the old values. The position of cat (i.e., pixel of image) is updated as using given (Eq. 14):

$$Po_{c,d} = Po_{k,d} + Ve_{k,d} \quad (14)$$

Step 4: Final fitness value considered as the optimal result and is updated in the proposed system. The Pseudo code of this algorithm is given below algorithm 1:

Algorithm 1: HCSO

Input: h, d, Ve, Po, r_1 , c_1 , F

Output: best optimal threshold

start

1. N cats are Generated
2. All the parameters are initialized for every cat (i.e., image pixel)
3. gbest with the lowest fitness cat Initialized in swarm
4. for each cat in swarm
 - Check if the flag of the chosen cat is tracing mode
 - Selected cat applied into tracing mode process
 - Else
 - Selected cat applied into tracing mode process
 - EndIf
 - Gbest s updated
 - End for
5. Number of cats re-picked and set them into tracing mode along with mixture ratio, and other cats set in seeking mode.
 - Check If the condition is to terminate, then complete the program
 - Otherwise repeat (Eq. 4) and (Eq. 5) steps process

End

Finally, the optimal threshold segmenting image is displayed with various vessel tracking results

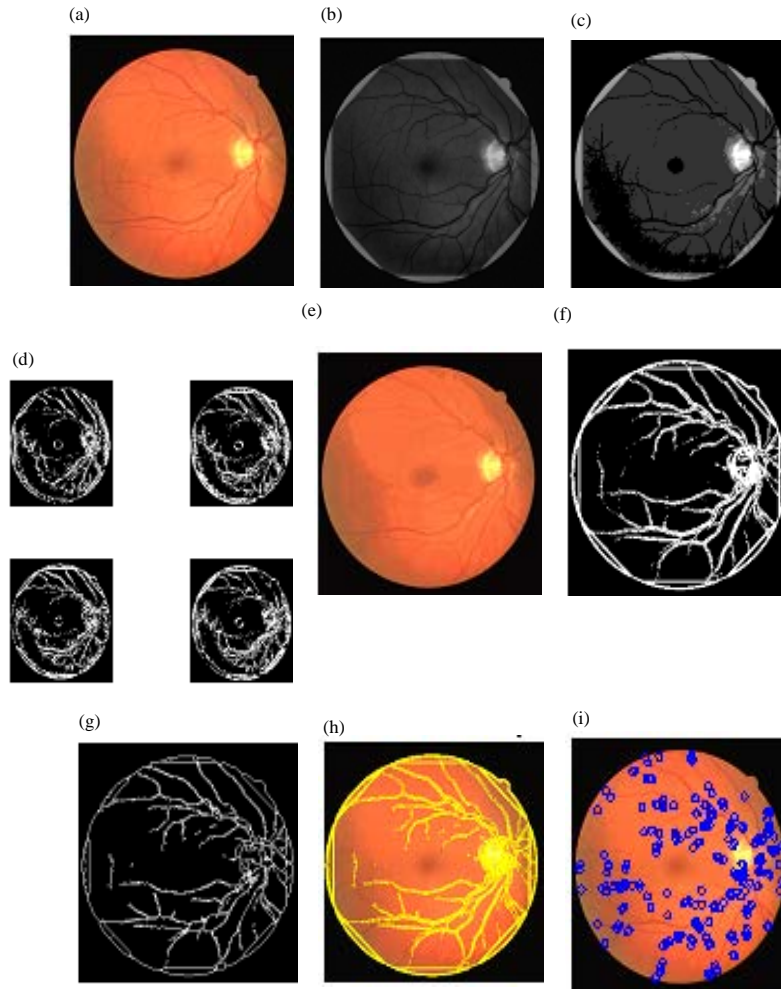


Fig. 3: Step by step process of proposed HCSO-MSC on DRIVE dataset; a: Input image; b: Preprocessed image; c: Feature extracted image; d: Feature extracted result (feature 1-4); e: Means shift; f: HCSO segmentation result; g: Skeletonised image; h: Segmentation with optimal threshold boundary and i: Different vessel extraction

RESULTS AND DISCUSSION

In this study, performance of proposed HCSO-MSC has been evaluated based on the publically available four datasets like DRIVE (Staal *et al.*, 2004), STARE (Hoover *et al.*, 2000), MESSIDOR (Anonymous, 2004) and VAMPIRE (Perez-Rovira *et al.*, 2011). The performance is measured by in terms of sensitivity, specificity, accuracy and AUC score. The simulation of proposed HCSO-MSC scheme performance is evaluated with existing hybrid Glow-worm Swarm Optimization and Bat (hybrid GSOB), hybrid Cuckoo Search with Artificial Fish Swarm (hybrid CS-AFS) and Flower Pollination Search Algorithm with Pattern Search (FPSA-PS) (Emary *et al.*, 2017).

Segmentation performance measures: To measure the performance of the proposed segmentation, four common

metrics are employed like sensitivity specificity accuracy and Area Under Curve (AUC). Sensitivity indicates the true positive rate, specificity defines the false positive rate and accuracy defined the correct prediction of vessel segmentation. The step by step evaluation of proposed scheme is evaluated for four data set and these results are showed in Fig. 3-7. These figures are shows the all stages like pre-processing, feature extraction and segmentation, optimal threshold selection, morphological skeletonization and vessel extraction of the tested images. The proposed scheme shows better output results compared than existing schemes due to the kernel connectivity and optimal threshold selection with efficient clustering. The clustering process can be improved the image quality, so, the output of vessel segmentation has get better result.

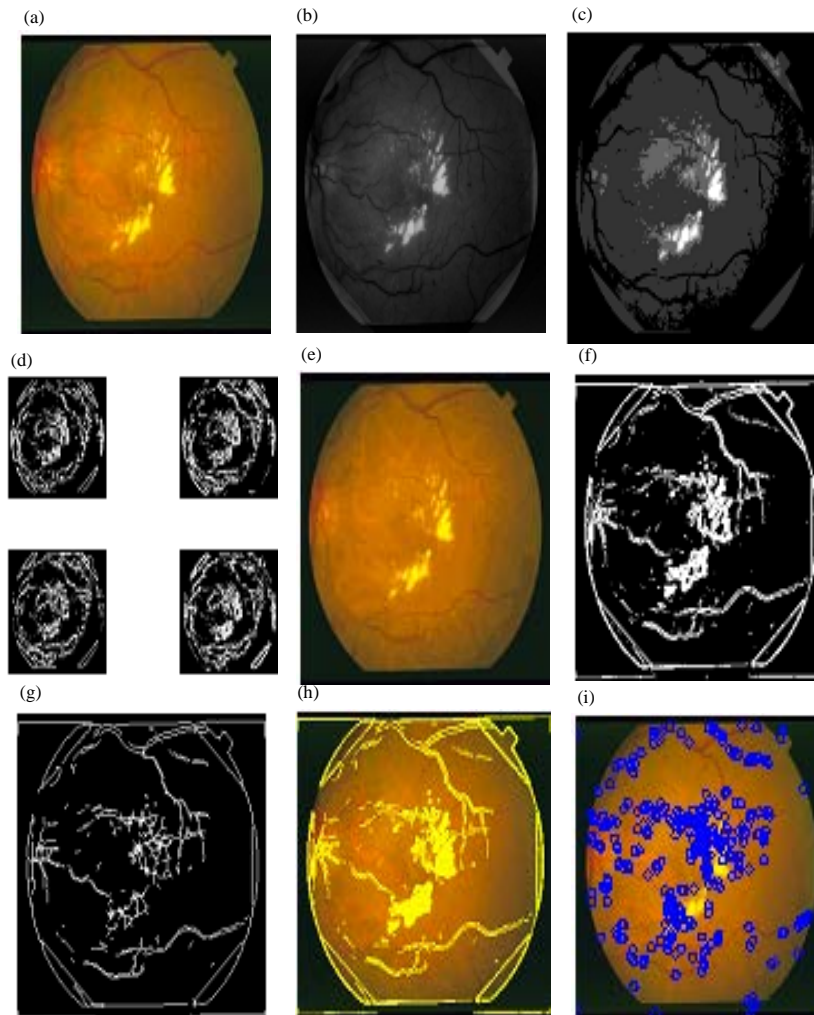


Fig. 4: Step by step process of proposed HCSO-MSC on STARE dataset; a: Input image; b: Preprocessed image; c: Feature extracted image; d: Feature extracted result (feature 1-4); e: Means shift; f: HCSO segmentation result; g: Skeletonised image; h: Segmentation with optimal threshold boundary and i: Different vessel extraction

Figure 6 shows the graph for threshold trace comparison between proposed HCSO-MSC and existing segmentation schemes. It illustrated the proposed scheme attained better threshold traces with accurately compared than existing hybrid CS-AFS, hybrid GSOB and FPSA-PS. Because the proposed scheme has good convergence speed and efficient feature extraction with good pre-processing results. The clustering process has improved the accuracy.

Figure 7 shows the graph of performance comparison of convergence speed for HCSO-MSC and existing segmentation schemes. It illustrated the proposed scheme attained efficient fitness compared than existing hybrid CS-AFS, hybrid GSOB and FPSA-PS. In proposed system, the efficient fitness increased the convergence

speed and increases the iterations the system has stable form compared than existing algorithms. Figure 8 shows the graph of performance comparison of all parameters for HCSO-MSC and existing segmentation schemes. It illustrated the proposed scheme attained efficient accuracy of 98.72%, sensitivity of 96.73%, specificity of 97.58 and AUC score of 97.63% compared than existing hybrid CS-AFS, hybrid GSOB and FPSA-PS. The proposed system has attained better performance due to the efficient feature extraction and optimization scheme with efficient clustering. When the number of images increased means the performance of proposed HCSO-MSC also increased with stable results. The performance of all parameters numerical values are defined in Table 1 (Fig. 9).

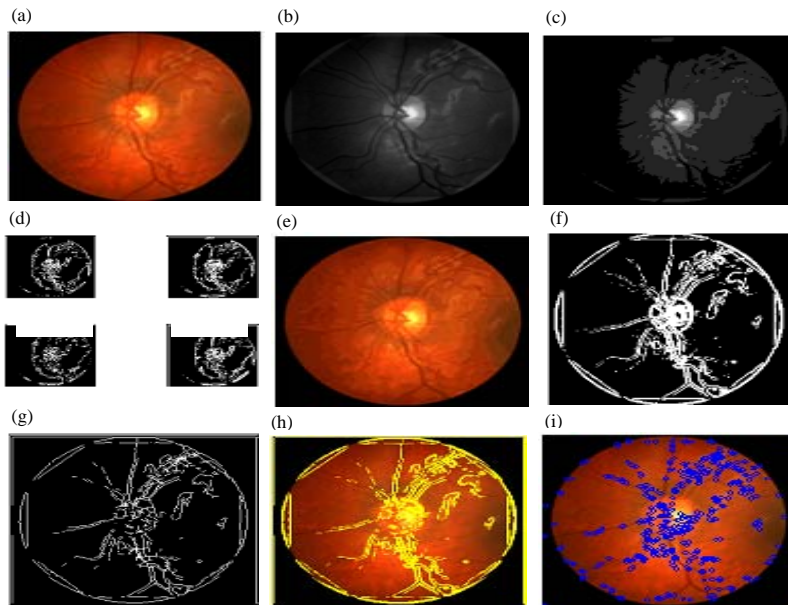


Fig. 5: Step by step process of proposed HCSO-MSC on MESSISOR dataset; a: Input image; b: Preprocessed image; c: Feature extracted image; d: Feature extracted result (feature 1-4); e: Means shift; f: HCSO segmentation result; g: Skeletonised image; h: Segmentation with optimal threshold boundary and i: Different vessel extraction

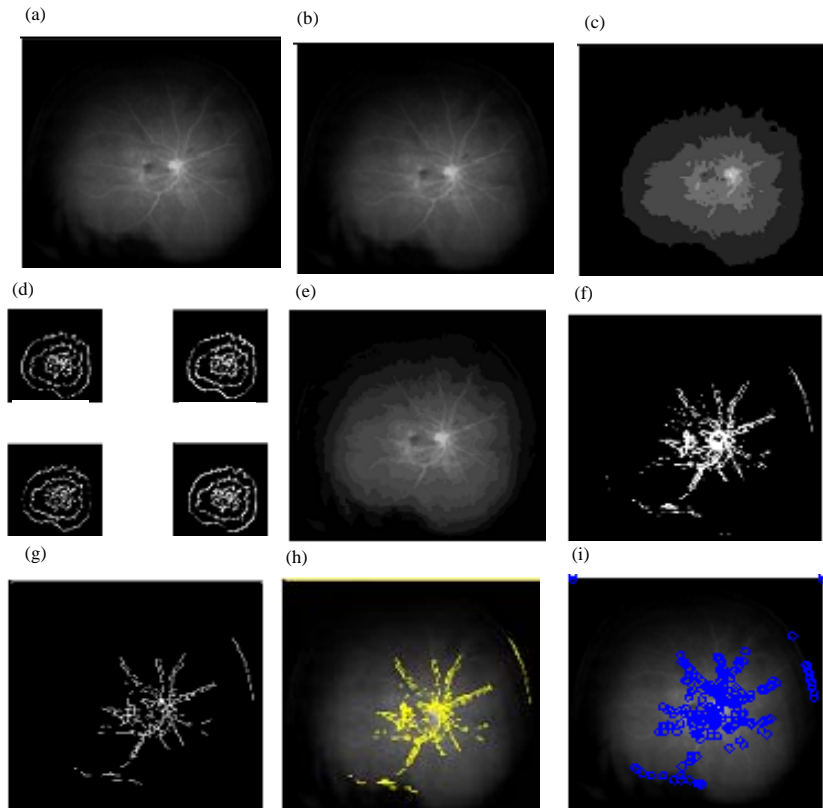


Fig. 6: Step by step process of proposed HCSO-MSC on VAMPIRE dataset; a: Input image; b: Preprocessed image; c: Feature extracted image; d: Feature extracted result (feature 1-4); e: Means shift; f: HCSO segmentation result; g: Skeletonised image; h: Segmentation with optimal threshold boundary and i: Different vessel extraction

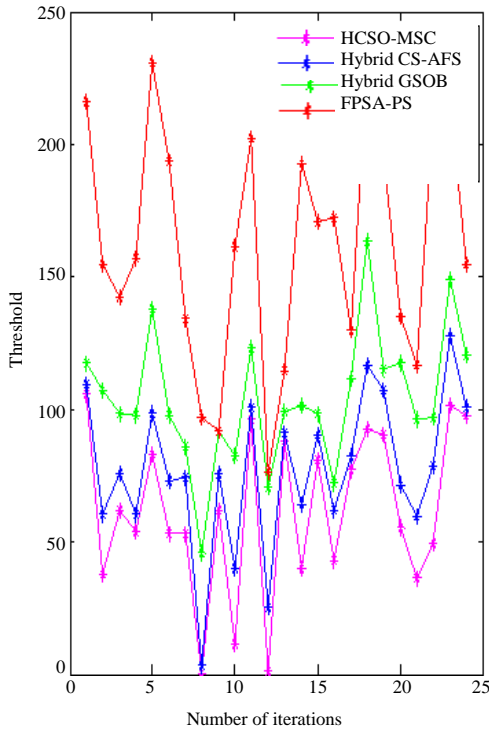


Fig. 7: Performance comparison of threshold traces for all segmentation schemes

Table 1: Performance of all parameters numerical values for proposed HCSO-MSO

Parameters	Performance value of proposed HCSO-MSO	Hybrid CS-AFS	Hybrid GSOB	FPSA-PS
Sensitivity	0.9673	0.9586	0.9413	0.9372
Specificity	0.9758	0.9615	0.9543	0.9021
Accuracy	0.9872	0.9787	0.9657	0.9421
AUC score	0.9763	0.9689	0.9479	0.9193

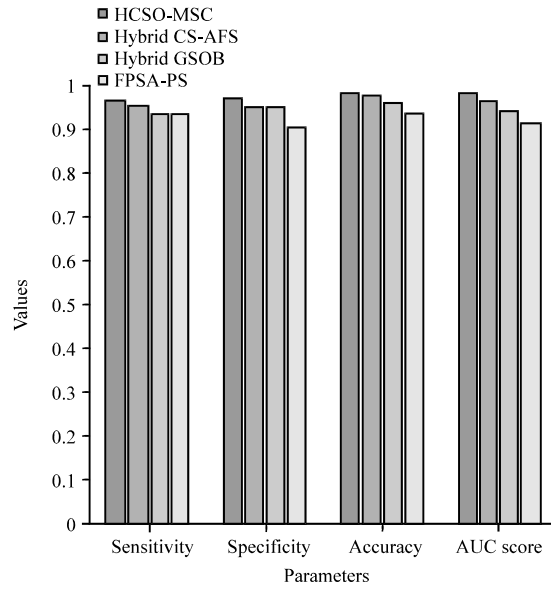


Fig. 9: Performance comparison for all parameters

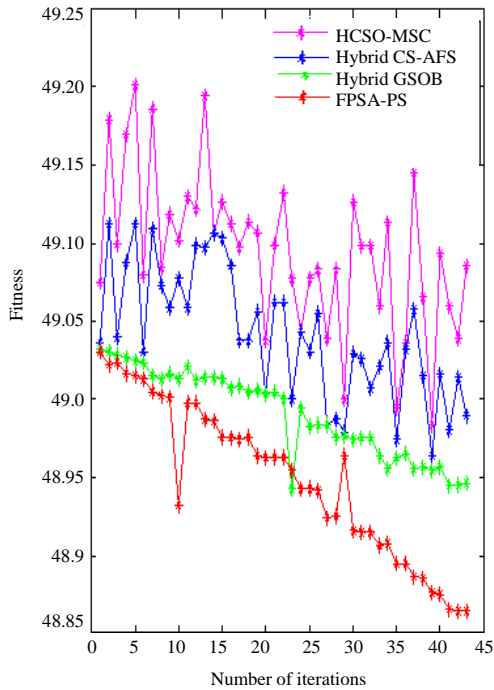


Fig. 8: Performance comparison of convergence speed for all segmentation schemes

CONCLUSION

In this study, an efficient HCSO with MSC algorithm is proposed for extracting the vessels from retinal image to diagnosis eye diseases. The input image is pre-processed using top hat filtering for improve the vessel segmentation accuracy. Then, the features are extracted efficiently using morphological approach for reducing the computational time. After that eigenvectors of affinity matrices are computed which are formed using the connectivity kernel. The Boltzmann equation based connectivity carried and it matches the statistical distribution of edge co-occurrence in natural images and it directs to the final grouping using MSC clustering scheme. Finally, the vessels are segmented using HCSO. In HCSO, all particles are arranged in a regular tree structure and move up or down in the tree based on their fitness value. The proposed scheme efficiently find the blood vessel junction position and the performance is evaluated for four data set. The experimental shows the overall performance of proposed HCSO-MSO scheme attained better results in terms of accuracy of 98.72%, sensitivity of 96.73%, specificity of 97.58 and AUC score of 97.63% compared than existing vessel segmentation schemes.

RECOMMENDATIONS

In future, this proposed algorithm will investigate an extension for more complex blood vessel structures, mainly in the liver. Some other measure also focused to evaluate the performance of the system and also focused post processing step to reduce discontinuities at bifurcations. It also evaluated for some other dataset and real time data's.

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