Vessel Tracking for Retina Images Based on Fuzzy Ant Colony Algorithm

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ABSTRACT

In this paper we present a novel fuzzy algorithm for vessel tracking in retina images. The main tools of this system are Ant Colony Optimization algorithm (ACO) and eigenvector analysis of Hessian matrix. ACO, inspired by food-searching behaviors of ants and performs well in discrete optimization, has been used for optimizing objective function of fuzzy C-means(FCM) model and clustering pixels into vessel and background clusters and Hessian matrix has been used for determining vessel direction in tracking process. Estimating full vessel parameters, overcoming initialization and profile modeling in related works and handling junction of vessels in retina image are the most important advantages of this method. Experiments and results of proposed algorithm in ocular fundus image show its good performance in vessel tracking and parameters estimating.

Keywords: Ant colony algorithm, Fuzzy clustering, Hessian matrix, Vessel tracking, Retina images

1 INTRODUCTION

The detection and measurement of blood vessels can be used to quantify the severity of disease, as part of the process of automated diagnosis of disease or in the assessment of the effect of therapy. Retinal blood vessels have been shown to change in diameter, branching angles or tortuosity as a result of a disease. Thus a reliable method of vessel segmentation would be valuable for the early detection and characterisation of morphological changes [1].

Vessel tracking is one of the common methods that are used in vessel segmentation. Most of vessel tracking methods begin from given initial points on the vessel and estimate the vessel width and orientation within a local region about the current point. Then a small step is taken along vessel direction and the procedure is repeated until stop conditions are satisfied. This method can calculate vessel centerline and diameter efficiently and provide a meaningful description of the vessel network. In the case of retina images, some works have been done according to this method that we can mention to [2-5]. In these papers, tracking was performed with respect to local information and tried to find maximum coincidence of vessels profile model.

In our retina processing system, we automatically initialize starting points from optic nerve in retina image and the profile that is centered in starting point is acquired at the direction normal to the direction of proper eigenvector of Hessian matrix in center point. Ant colony algorithm, which is a novel method to minimize objective function of FCM model and known as ACO-FCM, is used for detection of vessel and background regions along vessel profile. The position of real center is calculated by finding weighted mean of profile pixel positions with membership function of vessel cluster as their weights. The next center point is approximated by using of vessel direction and look-ahead distance which is proportional to vessel diameter.

The remaining of this paper is organized as follows: Section 2 provides a brief description of the Ant colony algorithm and its fuzzy application. Section 3 gives an overview of eigenvector analysis of Hessian matrix. Section 4 represents the proposed vessel tracking algorithm. In section 5, the experimental results are described and finally we express conclusions.

2 ACO-FCM CLUSTERING

Ant colony optimization was originally introduced by Dorigo and Maniezzo in 1996 [6]. In their original work, an optimization algorithm called *ant system* was introduced and applied to discrete optimization problems such as the traveling salesman problem (TPS). After this original article many other applications of ACO were reported [7].

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The main idea in ACO is to mimic the behavior of real biological ants in search of food. The ants are able to efficiently find the shortest path from the nest to the food source and back. Ants deposit *pheromone* trails along their paths depending on the length of the trail (the shorter the trail, the more pheromones are deposited) and ant moves more or less randomly, but prefers locations with higher pheromone concentrations. The pheromones evaporate over time; hence the paths can be abandoned if they were not preferred during time. The ACO algorithm imitates these mechanisms by choosing solutions based on pheromones and updating pheromones according to the solution quality (and evaporation) [7]. More information about ant systems can be found in [8].

In traditional FCM model for clustering, a dataset $X = \{x_1, \dots, x_n\}$ is classified into $c \in \{2, \dots, n-1\}$ clusters that the following objective function must be minimized:

$$J(U,V) = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^{m} d_{ik}^{2} \tag{1}$$

where U is the fuzzy partition matrix, $V = \{v_1, \dots, v_c\}$ is cluster centers vector, $c \geq 2$ is the number of clusters of final partition, n is the number of available data, the elements $u_{ik} \in [0,1]$ of U represent the membership of data object x_k in cluster i, $m > 1$ is the *fuzzifier* that controls the fuzziness of the final partition, $d_{ik} = \|v_i - x_k\|$ is a distance metric between the data vector x_k and cluster center v_i.

The FCM clustering algorithm calculates partition matrix $U \in M_{fcm}$, where:

$$M_{fcm} = \left\{ \left(U \in [0,1]^{c \times n} \middle| \sum_{i=1}^{c} u_{ik} = 1\,, k = 1, \dots, n, \sum_{k=1}^{n} u_{ik} > 0, i = 1, \dots, c \right) \right\}. \tag{2}$$

It can be shown that the necessary conditions for local minimum of objective function $J(U,V)$ are

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^{m} x_k}{\sum_{k=1}^{n} u_{ik}^{m}} \qquad u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{d_{ik}}{d_{jk}} \right)^{2/(m-1)}} \tag{3,4}$$

In 2005 Thomas A. Runkler [7] showed, by applying ACO-FCM algorithm to two types of databases, that FCM model optimized by ACO has better outcome than traditional optimization algorithm. In this algorithm each ant represents one of the data points $x_k \in X$ and assigns it to one of the C clusters based on a pheromone matrix $P \in R^{c \times n}$. Each entry in the pheromone matrix P represents one entry in the partition matrix U. The basic idea is to randomly produce fuzzy partition $U \in M_{fcm}$ whose excepted value approximately corresponds to the normalized pheromone matrix P. This is done by adding Gaussian noise with variance σ to the normalized matrix P. After calculating objective function, pheromones matrix is updated according to evaporation rate and pheromone update function as following:

$$P_{ik} = P_{ik} \times (1-\rho) + u_{ik} / (J(U,V) - J(U,V)_{min} + \varepsilon)^{\alpha} \tag{5}$$

where ρ is evaporation rate, $\varepsilon > 0$ and $\alpha > 1$ are user-specified parameters and $J(U,V)_{min}$ is minimum objective function which has ever been achieved. In any iteration that $J(U,V)$ is more than $J(U,V)_{min}$, P_{ik} is updated based on difference between $J(U,V)$ and $J(U,V)_{min}$ otherwise we have $J(U,V)_{min} = J(U,V)$ if $J(U,V)$ is less than $J(U,V)_{min}$, therefore, P_{ik} does not have very changes. The resulting ACO-FCM algorithm is summarized in Fig. 1.

3 EIGENANALYSIS OF THE HESSIAN MATRIX

Application of Hessian matrix to detect and analyze line-like structures has been investigated in many literatures and it is also used for segmentation and visualization of curvilinear structures in medical images [9,10]. The Hessian matrix is defined as:

$$H = \begin{bmatrix} I_{xx} & I_{xy} \\ I_{yx} & I_{yy} \end{bmatrix}. \tag{6}$$

Here, the second-order spatial derivative I_{ab} is calculated by convolution between the input image and scaled second-order derivative of Gaussian filter:

$$G(x,y;\sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}. \tag{7}$$

The eigenvalues and eigenvectors of Hessian matrix denote vessel's intensity and direction properties. Let λ_1 and λ_2 be the eigenvalues of Hessian matrix in given point as $|\lambda_1| \leq |\lambda_2|$ and v_1 and v_2 be the corresponding eigenvectors. It can be shown that vector v_1 is parallel to vessel axis-line while v_2 is perpendicular to that.

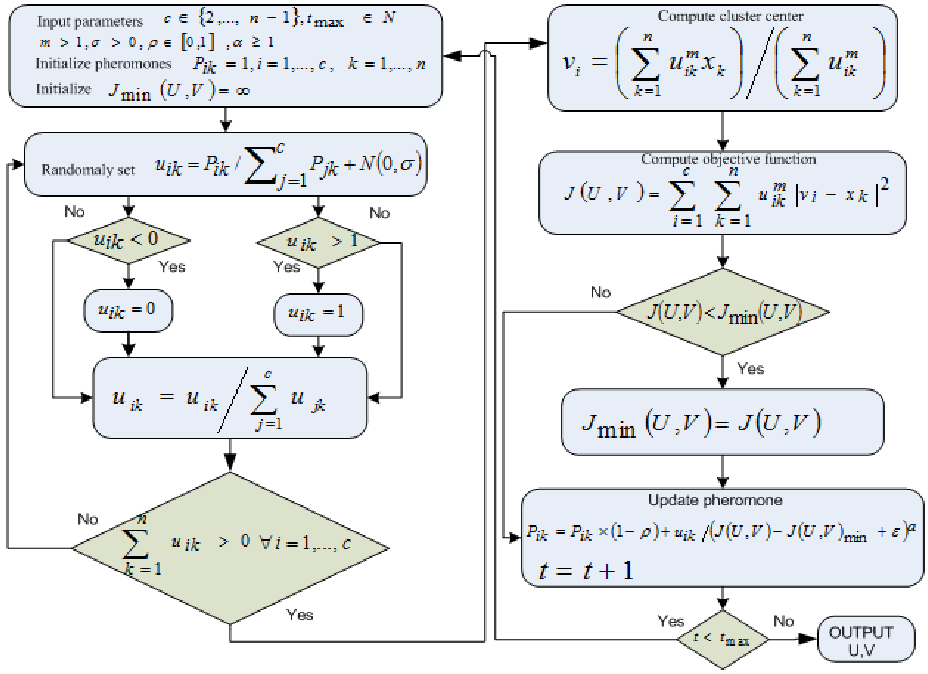

Figure 1. Flowchart of ACO-FCM algorithm

4 PROPOSED APPROACH

4.1 Initialization

There are some papers explaining how optic nerve can be found in retina images [11, 12]. These papers can be used to initialize algorithm. Having found the optic nerve, we form a sequence of points belonging to circle that bounds optic nerve. They are classified into vessel and background clusters by ACO-FCM algorithm. Each region in sequence that has more than three points with high membership degree in vessel cluster is considered as vessel candidate for starting the tracking process [5]. Center point of each region and its eigenvector of Hessian matrix in that point are defined as initial center pixel of vessel and its direction, respectively. False candidate points will be omitted within tracking algorithm.

4.2 Tracking process

The tracking will be started with initial points and its proper eigenvector of Hessian matrix. Let C_k be a pixel on vessel centerline in current iteration and v_k be eigenvector of Hessian matrix in center point that v_k is parallel to vessel direction. The location of center point in next iteration, C'_{k+1}, is calculated by:

$$C'_{k+1} = C_k + D_k v_k \tag{8}$$

where D_k is look-ahead distance parameter and it is proportional to vessel diameter in pervious iteration.

Centered at this position, a profile vector P is obtained by sampling of gray-scale values pixels along a scanline perpendicular to the direction of eigenvector in current center position v'_{k+1}. The length of profile is adapted to vessel diameter and is considered three times as much as vessel diameter in our work. The pixels gray-scale values of profile are classified into vessel and background clusters by ACO-FCM algorithm and center point of vessel is calculation by finding weighted mean of profile pixel position with membership function of vessel cluster as their weights:

$$\tilde{C}_{k+1} = \frac{\sum_{i=1}^{n} m_{vessel}(i) \times P(i)}{\sum_{i=1}^{n} m_{vessel}(i)} \tag{9}$$

where m_{vessel} denotes membership function of vessel cluster.

In order to compensate vessel changes in situations that it has high curvature and adjust center point between two edges, the profile P is obtained again with $\tilde{C}_{k+1}$ and $\tilde{v}_{k+1}$ as its center point and normal direction, respectively, that it is suggested by Sun [13] in 1989. The ACO-FCM classifies new profile and final center point is calculated by Equation (9). Right and left edge can be estimated as positions which have vessel and background

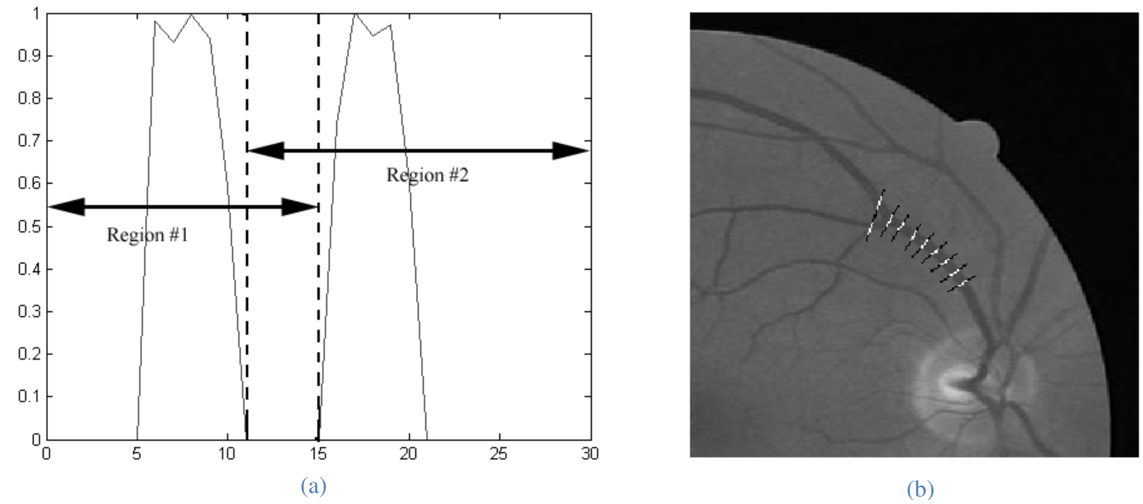

Figure 2. (a) The vessel membership function in bimodal state and two regions for calculating centers and (b) detection of junction corresponding to it.

membership functions almost equal in profile and vessel diameter is defined as distance between right and left edges.

4.3 Junctions

When algorithm confronts junctions in its tracking, the profile becomes bimodal. In these cases, profile is separated into two regions in order to choose better path as Fig. 2(a). After each part is classified by ACA-FCM, its center is calculated by Equation (9) and the center point which its eigenvector of Hessian matrix has less angle with vessel direction in last valid profile is selected as next center point to continue tracking and the other center point is stored to be processed later.

4.4 stopping criterion

When vessel diameter is less than a specified threshold or right and left edges become very close, the algorithm terminates and stores centers points, right and left edges and diameters as vessel attributes and processes another initial point.

5 RESULTS AND DISCUSION

This algorithm has two groups of parameters. The first group is the ones belonging to ACO-FCM algorithm ($m, \sigma, \varepsilon, \alpha, \rho, t_{max}$) and the other is tracking parameters (look-ahead, profile size). The value of fuzzifier m for calculating the partitions is set to 2. This is the value that is usually used in the literature. σ is the variance of Gaussian noise added to the normalized pheromone matrix while $\varepsilon>0$ and $\alpha>1$ are user-specified parameters for updating pheromone matrix. An important parameter in ACO-FCM is evaporation rate (ρ). If ρ is chosen very high, pheromones matrix in Equation (5) will be affected by random numbers (u_{ik}) and worse results will be obtained. t_{max} is the iteration number of ACO-FCM and it must be high enough for decreasing objective function. The values of objective function versus the number of iteration have been shown in Fig. 3. In the second group, look-ahead distance influences computation time and it might miss several junction if it is selected large, hence, it is proportional to vessel diameter in pervious iteration. A fixed, large profile size would facilitate the detection of junction. However, in the case of vessels having small diameter the clustering algorithm would not provide valid cluster descriptions, therefore, the profile size is flexible and it is three times as much as last valid vessel diameter.

The vessel center and edge points of retina subimage extracted by algorithm are shown in Fig. 4. when $t_{max} = 1000, \rho = 0.25, \varepsilon = 0.01, \sigma = 0.001, m = 2$.

6 CONCLUSIONS

In this paper we have investigated the tracking of blood vessels in retina images. The proposed tracking scheme does not need any user interaction or any model for vessel profile. As well as it efficiently handles junctions of vessels in angiograms. The initial points are automatically obtained from optic nerve and ACO-FCM is used to classify pixel along vessel profile, which is normal to vessel orientation obtained by eigenanalysis of the Hessian matrix, into vessel and background cluster. In addition, vessel parameters such as centerlines, edge lines and

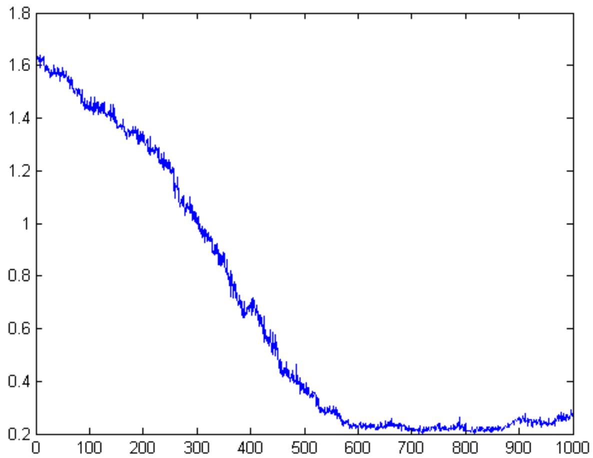

Figure 3. decreasing of objective function in one specific run of ACO-FCM

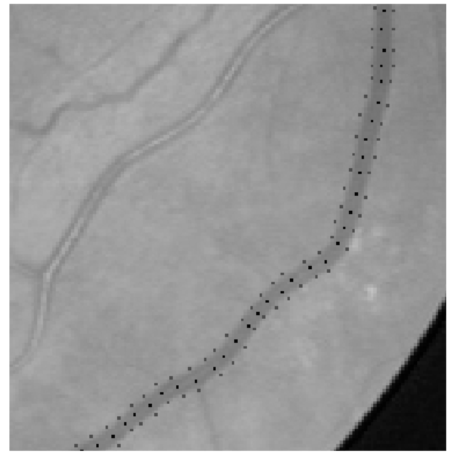

Figure 4. The main result of proposed algorithm

diameters are calculated by proposed algorithm. The results demonstrate the good performance of method in the whole tracking process and detecting more complete vessel network in the ocular fundus photographs.

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