Retinal vessel segmentation based on flower pollination search algorithm

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Abstract. This paper presents an automated retinal blood vessels segmentation approach based on flower pollination search algorithm (FPSA). The flower pollination search is a new algorithm based on the flower pollination process of flowering plants. The FPSA searches for the optimal clustering of the given retinal image into compact clusters under some constrains. Shape features are used to further enhance the clustering results using local search method. The proposed retinal blood vessels approach is tested on a publicly available databases DRIVE a of retinal images. The results demonstrate that the performance of the proposed approach is comparable with state of the art techniques in terms of accuracy, sensitivity and specificity.

Keywords: Flower Pollination Search Algorithm, Pattern Search, Retinal Vessel Segmentation, Computer Aided Diagnosis

1 Introduction

The automated retinal vessels segmentation is commonly accepted by the medical community as a first step for any computer-aided diagnosis system development [1]. Also retinal vessels segmentation is must for evaluation of retinopathy of prematurity [6], vessel abnormalities caused by multiple diseases such as obesity [2], hypertension [3], glaucoma [4] and diabetic retinopathy [5], vessel diameter measurement [7], fovea region detection [8], arteriolar narrowing [9] and computer assisted laser surgery [10]. The retinal vasculature is composed of arteries and veins appearing as elongated features, with their tributaries visible within the retinal image. other structures appearing in ocular fundus images include the retina boundary, the optic disc, and pathologies in the form of cotton wool spots, bright and dark lesions and exudates. The vessels can be expected to be connected and, in the retina, form a binary tree-like structure. However, the shape, size and local grey level of blood vessels can vary hugely and some background features may have similar attributes to vessels. Signal noise, drift in image intensity and lack of image contrast pose significant challenges to the extraction of blood vessels. Retinal vessels also show an evidence of a strong reflection along their centerline known as a central vessel reflex, which is more apparent in arteries than veins [11].

In this paper, a novel algorithm for automated segmentation of retinal vessels based on multi-objective segmentation is proposed. The proposed algorithm makes use two levels of clustering in the first level the flower pollination search algorithm (FPSA) searches for optimal vessels of retina. In the second level of optimization the obtained cluster center are much enhanced using local search but now the target is to localize the thin or vessels with small diameters. The experimental results of the novel algorithm was assessed on the DRIVE database [12] and proves good performance.

The rest of this paper is organized as follows: Section 2 discusses the flower pollination search algorithm. Section 3 discusses the localizing vessels with flower pollination search algorithm and pattern search approach including its all phases. Section 4 shows experimental results and analysis for the performance of proposed algorithm. Finally, section 5 addresses conclusions and discusses future work.

2 Flower pollination search algorithm (FPSA)

The flower pollination search is an algorithm based on the flower pollination process of flowering plants [13]. The main purpose of a flower is ultimately reproduction via pollination. Flower pollination is typically associated with the transfer of pollen, and such transfer is often linked with pollinators such as insects, birds, bats and other animals. Pollination can be achieved by *self-pollination* or *cross-pollination*. *Cross-pollination*, or allogamy, means pollination can occur from pollen of a flower of different plant, while *self-pollination* is the fertilization of one flower, such as peach flowers, from pollen of the same flower or different flowers of the same plant, which often occurs when there is no reliable pollinator available. Biotic, cross-pollination may occur at long distance, and the pollinators such as bees, bats, birds and flies can fly a long distance, thus they can considered as the global pollination. In addition, bees and birds may behave as Levy flight behaviour [14], with jump or fly distance steps obey a Levy distribution. Furthermore, flower constancy can be used an increment step using the similarity or difference of two flowers.

Yang in [13] idealized the above characteristics of pollination process, flower constancy and pollinator behaviour in the following rules: (a) Biotic and cross-pollination is considered as global pollination process with pollen carrying pollinators performing Levy flights, (b) Abiotic and self-pollination are considered as local pollination, (c) Flower constancy can be considered as the reproduction probability is proportional to the similarity of two flowers involved, and (d) Local pollination and global pollination is controlled by a switch probability $p \in [0,1]$.

Due to the physical proximity and other factors such as wind, local pollination can have a significant fraction p in the overall pollination activities. In the global pollination step, flower pollens are carried by pollinators such as insects, and pollens can travel over a long distance. This ensures the pollination and reproduction of the most fittest, and thus we represent the most fittest as g_*. The first rule can be formulated as bee is updated using the equation 1:

$$X_i^{t+1} = X_i^t + L(X_i^t - g_*) \tag{1}$$

Where X_i^t is the solution vector i at iteration t, g_* is the current best solution, and L is the strength of the pollination which is a step size randomly drawn from Levy distribution. The local pollination (Rule 2) and flower constancy can be represented as in equation 2.

$$X_i^{t+1} = X_i^t + \varepsilon(X_j^t - g_k^t) \tag{2}$$

Where X_j^t and g_k^t are solution vectors drawn randomly from the solution set. The parameter ε is drawn from uniform distribution in the range from 0 to 1.

3 FPSA-PS multi-objective vessel localization approach

The system for localizing vessels with flower pollination search algorithm and pattern search (FPSA-PS) cluster is composed of three main phases namely *preprocessing*, *segmentation*, and *post-processing*. These three phases are described in detail in the following section along with the steps involved and the characteristics feature for each phase.

3.1 The preprocessing phase

In the preprocessing phase the green band is selected for the analysis as it much highlight the vessels more than the other bands. To get a more brightness corrected image so that the average brightness is equalized that may affect the segmentation algorithm we applied brightness correction. The method simply calculates the global mean of the brightness *gMean* over the whole image and hence passes over the image by a window with large size to ensure that the mean brightness inside the window *wMean* is proportional to the global mean *gMean*. The new brightness value for the center pixel of the window is calculated as in equation .

$$Pixel\ Brightness = \frac{Pixel\ Brightness}{wMean} * gMean \tag{3}$$

3.2 The vessel segmentation algorithm

The vessel segmentation algorithm can be divided into two main phases namely global spectral clustering and local shape clustering.

Global spectral clustering: The flower search algorithm is a global search method that search a space of n-D for an optimal of a given fitness function. The fitness function generally in the clustering encodes the intra-cluster compactness. Equation 4 is an example of fitness function for clustering that was used in the K-means clustering [15].

$$J = \sum_{j=1}^{x} \sum_{i=1}^{k} ||x_i^j - c_j||^2 \tag{4}$$

Where $||x_i^j - c_j||^2$ is a distance measure between a data point and the cluster center, and an indicator of the distance of the n data points from their respective cluster centers.

A much enhanced fitness function that considers the partial belongness of the data point to the clusters was used in the fuzzy c-means clustering [16] in equation 5.

$$minJ(M, v_1, v_2, ...v_c) = \sum_{i=1}^{c} \sum_{k=1}^{n} (\mu_{ik})^q (d_{ik})^2 \tag{5}$$

Where q is weighting exponent parameter and it controls the extend of membership sharing between fuzzy clusters and μ_{ik} is calculated as in equation 6. d_{ik} is calculated as the distance between the data point and a cluster center as in equation 7 and the cluster centers are calculated as in equation 8.

$$\mu_{ik} = [\sum_{j=1}^{c} (\frac{d_{ik}}{d_{jk}})^{\frac{2}{q-1}}]^{-1} \tag{6}$$

$$d_{ik} = \|x_k - v_i\| = [\sum_{j=1}^{m} (x_{kj} - v_{ij})^2]^{\frac{1}{2}} \tag{7}$$

$$v_i = \frac{\sum_{k=1}^{n} (\mu_{ik})^q \cdot x_k}{\sum_{k=1}^{n} (\mu_{ik})^q} \tag{8}$$

Where $x_k = k^{th}$ data point (possibly m dimensional vector and $k = 1, 2, ...c$), $v_i =$ the center of the i^{th} fuzzy cluster ($i = 1, 2, ...c$).

It worth mentioning that the fitness function in 6 imposes a constrain on the sum of belongness of a data point to all clusters to 1; see equation 9.

$$\sum_{i=1}^{c} \mu_{ik} = 1 \tag{9}$$

Where k is any sample point in the data to be clustered.

The FCM fitness assigns memberships to objects which are inversely related to the relative distance of the point prototypes that are cluster centres. Suppose if an object is equidistant from two prototypes, the membership of it in each cluster will be the same, apart from the absolute value of the distance from the two centroids (as well as from the other points in the data). The dilemma created due to this is the noise points, that are far but equidistant from the central structure of the two clusters, can however be given equal membership in both the clusters, when it appears far more usual to give such points very low (or even no) membership in either clusters.

The solution to the dilemma is to relax the column sum constraint equal to one, so that the sum of each column satisfies the looser constraint. In other words, each element of the $i^t h$ column can be any number between 0 and 1. suggested that in this case the value should be interpreted as the typicality, relative to the cluster (rather than its membership in the cluster). The modified fitness function proposed in [17] is used in this paper. The output of this spectral clustering phase is the cluster centers where the darkest cluster center represents the vessel pixels.

local shape clustering: When the FPSA converges, the obtained centers are used as initial solution of the *PS local search*. The target now is to update the obtained cluster centers so that it maximizes the resulted vessel binary image total *thinness measure*. The thinness measures is used as indicator for the goodness of the obtained binary image since vessels with small diameter are much highlighted using this measure. The second phase of optimization can be considered as some sort of binary image constrained closing but it regards the original pixel gray level and the closeness of the connected pixels and tries to search for thin connected components. The thinness measure is outlined in the equation 10.

$$T = \frac{4\pi * A_i}{P_i^2} \tag{10}$$

Where A_i is the total area of individual connected components and P_i is the total perimeter of individual connected components. In the local search phase the search space is much more limited than the search space for the global search

3.3 The post-processing phase

The postprocessing targets at removing tiny individual connected components, close tiny gaps and connected component with small thinness ratio. To remove tiny connected components and fill small gaps we made use of rank order filter with size 3*3 and rank 5. Binary connected components with thinness ratio less than a specified threshold are removed see equation 10. This measure is around 1 for circular shaped connected components and larger for thin connected components.

4 Experimental results and discussion

Digital Retinal Images for Vessel Extraction (DRIVE) database [12] is used for assessment of the proposed algorithm performance. The DRIVE data set consists of 40 images (768*584, eight bits per channel). The images are in compressed JPEG format and have been divided into a training and a test set, each containing 20 images. The field of view (FOV) is approximately 50^o. In this section results for flower pollination search algorithm (FPSA) is compared to the results of FPSA-PS segmentation on the DRIVE data set. Different fitness functions are tried to both the FPSA and FPSA-PS segmentation on different number of evaluations and results are outlined. Figure 1 outlines the resulted vessel map resulted from the FPSA algorithm; in the red band, and the FS-PS algorithm; in the green band. We can remark from the figure that the PS local search moves cluster center towards getting much thin connected components and hence can localize minor tributaries. Table 1 proves the robustness of the proposed method where we can see that the performance on all images of the DRIVE database is comparable

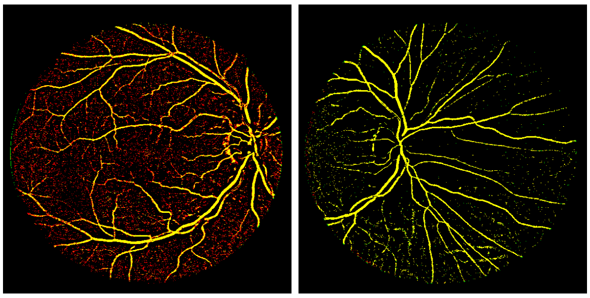
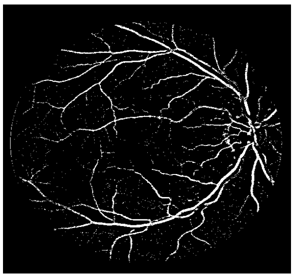
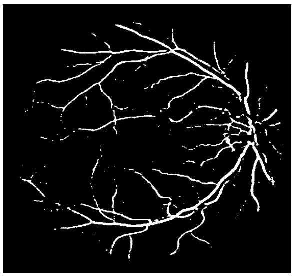


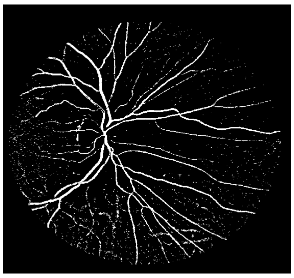
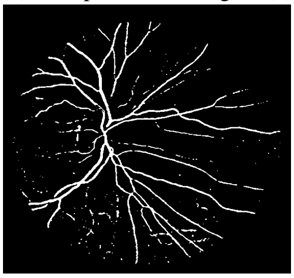
Fig. 1. FPSA and FPSA-PS in PFCM fitness function results

Table 1. Performance evaluation of the FPSA-PS segmentation results.

imNum	TP	TN	FP	FN	Acc
1	21657	184034	4506	7783	94.362
2	23306	182318	2563	10484	94.034
3	17105	184988	1432	15788	92.148
4	16204	190091	700	14150	93.285
5	16721	189460	885	14191	93.186
6	17630	187503	1447	14486	92.793
7	14667	190286	799	15485	92.64
8	12610	189060	1392	15779	92.154
9	12891	193626	856	13850	93.352
10	12608	193176	553	14548	93.163
11	18509	189679	2159	11030	94.042
12	17659	190251	2433	10831	94.003
13	20509	185618	3183	11750	93.245
14	17431	189750	3020	9246	94.41
15	15215	194531	2817	8399	94.924
16	15309	190596	866	14482	93.063
17	16037	189595	2020	11815	93.696
18	17368	191832	3204	8776	94.584
19	20586	191011	2570	6785	95.766
20	15067	194355	2465	9198	94.725
Total	339089	3791760	39870	238856	
	89.4790	94.0739	10.5209	5.92604	93.6790

(a) FPSA-PS result on normal image (b) Post-processed image in(a)

(c) FPSA-PS result on abnormal image (b) Post-processed image in (c)

Fig. 2. Post-processing results

regardless of whether the image is normal or abnormal.

Figure 2 outlines samples for normal and abnormal cases drawn from DRIVE database before and after post-processing. We can remark that the proposed post-processing steps removes tiny pixels using the median filter and also small gaps are filled thanks to the use of closing morphological operator.

5 Conclusions and future work

A system for retinal vessel segmentation was proposed using the flower pollination search algorithm (FPSA) to localize the retinal vessel map that uses the possiblistic fuzzy c-means (PFCM) fitness function. The obtained cluster center are much enhanced by adding vessel shape description to the fitness function and making use of local search to find the new enhanced cluster centers. The results proves the fast convergence of the flower pollination search algorithm (FPSA) and the robustness of the obtained results even with image with abnormalities. Other constrains on the vessel shape and vessel probability can be added to the fitness function to enhance the results in the future which is expected to further enhance the results.

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