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Retinal blood vessel segmentation approach based on mathematical morphology

Gehad Hassan[a,e,*], Nashwa El-Bendary[b,e], Aboul Ella Hassanien[c,d,e], Ali Fahmy[c], Abullah M.Shoeb[a], and Vaclav Snasel[f]

[a] *Faculty of Computers & Information, Fayoum University, Fayoum, 63511, Egypt*
[b] *Arab Academy for Science, Technology, and Maritime Transport, Dokki, Giza,12311, Egypt*
[c] *Faculty of Computers & Information, Cairo University, 5 Ahmed Zewal St., Orman, Giza, Egypt*
[d] *Faculty of Computers & Information, Beni Suef University, Beni Suef, Egypt*
[e] *Scientific Research Group in Egypt (SRGE), http://www.egyptscience.net*
[f] *Faculty of Electrical Engineering and Computer Science, VÅB-TU of Ostrava, Czech Republic*

Abstract

Diabetic retinopathy is a disease, which forms a severe threat on sight. It may reach to blindness among working age people. By analysing and detecting of vasculature structures in retinal images, we can early detect the diabetes in advanced stages by comparison of its states of retinal blood vessels. In this paper, we present blood vessel segmentation approach, which can be used in computer based retinal image analysis to extract the retinal image vessels. Mathematical morphology and K-means clustering are used to segment the vessels. To enhance the blood vessels and suppress the background information, we perform smoothing operation on the retinal image using mathematical morphology. Then the enhanced image is segmented using K-means clustering algorithm. The proposed approach is tested on the DRIVE dataset and is compared with alternative approaches. Experimental results obtained by the proposed approach showed that it is effective as it achieved average accuracy of 95.10% and best accuracy of 96.25%.

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Keywords: blood vessel extraction; k-means clustering; mathematical morphology; vessel segmentation; retinal image.

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* Corresponding author: Gehad Hassan
E-mail address: gehad_hassan_cs@yahoo.com

1. Introduction

Among the modern health care community, medical imaging has become the most important tool; this is because of the visual documentation and record storing for the patients and for its ability to information extraction about many diseases. For retinal image analysis, there are several applications, such as diabetic retinopathy, where it can be used in addition to their important roles in some diseases detection in early stages [1, 2]. Because of segmentation of retinal image structures using in modern ophthalmology as a non-invasive diagnosis; it has been a very interested topic. For retinal diseases such as hypertension, diabetic retinopathy, hemorrhages, macular degeneration, glaucoma, neo-vascularization and vein occlusion, working on the optic disc and the retinal blood vessel morphology is one of the basic indicators for assessing the presence and severity for each of these diseases. Assessment of the retinal blood vessels diameter and tortuosity or the optic disc shape manually has many disadvantages such as, time consuming and prone with human error, especially with complicated vessel structure and a large number of images [3].

Some of diseases listed above such as glaucoma, diabetic retinopathy, and macular degeneration are very dangerous. If they aren't detected correctly and in time, they can lead to blindness. Therefore, an accurate automated segmentation approach for retinal blood vessel and optic disc is a very important issue in computer aided-diagnosis [2]. The automation of segmentation and investigation of retinal blood vessel features helps ophthalmologist and eye care specialists to carry out mass vision screening exams for retinal diseases detection in early stages and treatment evaluation. This could help at prevention and reduction of vision impairments; age related diseases and many cardiovascular diseases as well as screening cost reduction [4].

This article presents an automated segmentation approach for retinal blood vessel. It based on some morphological operation and k-means algorithm.
The rest of this article is organized as follows: Section 2 presents the related works about our approach, their methodologies and the differences between them. Section 3 presents the core concepts of morphological processing and K-means algorithm. Section 4 describes the different phases of the proposed content-based segmentation system; namely mathematical morphology pre-processing, and classification phases using K-means. Section 5 discusses the tested image dataset and presented the obtained experimental results. Finally, Section 6 presents conclusions and future work.

2. Related Work

Many different algorithms were deployed for vessels segmentation, which achieved various results and performances. Fraz, Rudnicka and Barman [5] introduced supervised method. Dual Gaussian is used; a collection of second derivative of Gaussian and Gabor filters, feature vector is generated using some morphological transformation. This feature vector gives information which helping on handling the normal vessels and the vessels with the central reflex. The proposed system achieved accuracy, sensitivity and specificity of 0.96, 0.74 and 0.98, respectively. A supervised method, Yin and Bourennane [6] introduced, they used this method for vessel segmentation taking into account vessel edge detection on the retinal image. To detect vessel edge points in this method, they with maximum a posteriori (MAP) as criterion. This method achieves sensitivity and specificity 0.7248 and 0.9666, respectively on DRIVE.

Another method is morphological processing which consist of techniques [7] dealing with digital image processing using mathematical morphology by applying some structure element (SE) to binary images and sometimes to gray-level images. Roychowdhury, Koozekanani and Parhi developed a novel three-stage blood vessel segmentation algorithm. The first stage is pre-processing by high-pass filtering then extracting a binary image and another binary image is reconstructed from morphologically enhanced image for the vessel regions. Next the major vessels are extracted which is common regions from these two images. Then the second stage, Gaussian Mixture Model (GMM) classifier is used to classify all pixels in the two binary images which are remained from previous stage .Set of 8 features are used in GMM which extracted depending on first and second order gradient images and pixel neighbourhood. Finally the last stage, both the vessels and the classified vessel pixels are combined .This method with accuracy of 0.952 on the DRIVE.

Marin [8] performed a neural network scheme for pixel classification; 7-D vector was computed. For training and classification, they used multi-layer feed forward neural network. There are five main layers, the first one is the input layer which consists of seven neurons, and the second three layers are the hidden layers consisting of fifteen neurons, finally the output layer which has one neuron. This method has average accuracy, sensitivity and specificity on the DRIVE database 0.9452, 0.7067 and 0.9801, respectively.

Morphological multi-scale enhancement method is also presented in [9]. For the extraction of the blood vessels in the angiogram; fuzzy filter and watershed transformation are used. Multi-scale non-linear morphology opening operators with structuring element which vary in size is used to estimate the background, and then the background is subtracted from the image to achieve the contrast normalization. A combined fuzzy morphological operation is applied on the normalized angiogram with twelve linear structuring elements with nine pixels length; the structuring element rotated every 150◦ between zero and 180◦. Thresholding the filtered image to obtain the vessel region, then for approximating the vessels centrelines, thinning operation is applied. Finally watershed techniques are applied on vessel centreline to detect the vessel boundaries.

In [10] an approach is presented which is combined unique vessel centrelines detection with morphological bit plane slicing. The first order derivative of a Gaussian filter is used in four directions to extract the centrelines, and then performing an average derivative and derivative signs with the extracted centrelines. Mathematical morphology has proven their worth as a brilliant technique for the blood vessels segmentation in the retina. Morphological multidirectional top-hat operation is applied on blood vessels gray-scale image with linear structure element to obtain the orientation map and shape, and then the enhanced vessels are subject to bit plane slicing. For obtaining the vessel tree, these maps are combined with the centrelines. This method has average accuracy, sensitivity and specificity on the DRIVE database 0.943, 0.715, 0.977, respectively.

In [11] fast discrete curvelet transform with multi-structure mathematical morphology is proposed. For contrast enhancement, FDCT is performed. For detecting the blood vessels edges, multi-structure morphological transformation is applied. Then morphological opening is applied on the result image to remove the false edges. Finally for obtaining the complete final vascular tree, a connected adaptive component analysis is applied. This method has average accuracy, sensitivity and specificity on the DRIVE database 0.946, 0.735, 0.979, respectively.

An automated enhancement and segmentation method for blood vessels is presented in [12]. This method decreases the optic disc influence and emphasizes the vessels by applying a morphological multidirectional top-hat transform with rotating structuring elements to the background of the retinal image. For producing a vessel response image and the final blood vessel tree, an improved multi-scale line detector is applied. As line detectors in the multi-scale detector have different line responses, the longer line detectors produce more vessel responses than the shorter line detectors. To set different weights for different scales, all the responses are combined by the improved multi-scale detector at different scales. This method has average accuracy, sensitivity and specificity on the DRIVE database 0.942, 0.735, 0.969, respectively.

Most of these approaches have their advantages and disadvantages, which distinguish it from other. A complete extraction of the vascular tree in the digital retinal image can be provided since all the possible vessel pixels have been searched across the whole image. However special hardware is required to be more suitable for large image dataset for these techniques which are computationally expensive. In some approaches a significant degradation in the performance is caused because of noise and lesions so to pick up this noise we perform the enhancement operation. So in the recognition operation we could get false vessel detection with helping of this operation. In our approach we focus on the preprocessing enhancement stage which has a perfect effect on segmentation step. We use morphological processing to enhance the digital retinal images to get more accurate results in segmentation process, our approach with accuracy, specificity and sensitivity of 96.25%, 97.99%, and 87.99%, respectively.

3. Preliminaries

3.1 Morphological processing

Theory: Morphology is branch of biology [5]; its concept is dealing with form and structure of plants and animals. Mathematical morphology extracts components of image which are useful for representing and describing the region shape such as boundaries, skeletons and the convex hull. Mathematical morphology is considered as powerful tool which solving many problems in image processing and computer vision. Erosion, dilation, closing and top- hat transformation are the basic morphological operations which are used to detect, modify and manipulate the features presented in the image based on their shapes [13]. Mathematical morphology is a series of morphological algebraic arithmetic operators. Structuring element (SE) is applied by morphological operators typically to binary images and sometimes can be extended to gray-level images. Selecting the proper structure element for our application; its shape and size is an important step in Strengthening or weakening the results. A structuring element can be any size and take any shape and has origin point. Expanding the objects by a specific structuring element is called dilation, filling holes, and connecting the disjoint regions, dilation of image **A** by structuring element **B** is denoted by **A ⊕ B**. The structuring element B is positioned with its origin at **(x,y)** and the new pixel value is determined using rule 1:

$$g(x,y) = \begin{cases} 1 & \text{B hits A} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

or in set language as shown in rule 2:

$$A \oplus B = \{Z | (\hat{B})_z \cap A \neq \emptyset\} \quad (2)$$

In contrast the erosion operation which shrinks the objects by a structuring element, erosion of image **A** by structuring element **B** is denoted by $\boldsymbol{A \ominus B}$. The structuring element **B** is positioned with its origin at **(x, y)** and the new pixel value is determined using in rule 3:

$$g(x,y) = \begin{cases} 1 & B\ fits\ A \\ 0 & otherwise \end{cases} \quad (3)$$

or in set language as shown in rule 4:

$$A \ominus B = \{Z | (\hat{B})_z \subseteq A\} \quad (4)$$

Other morphological operations can be applied by performing a series of erosions and dilations, these operations called compound operations, the most widely used of these compound operations are opening and closing.

The opening of image A by structuring element B is denoted by A ∘ B is simply erosion followed by dilation as shown in rule 5 and rule 6.

$$A \circ B = (A \ominus B) \oplus B \quad (5)$$

$$A \circ B = \cup \{(B)_z | (B)_z \subseteq A\} \quad (6)$$

The closing of image A by structuring element B is denoted by A • B is simply a dilation followed by erosion as shown in rule 7.

$$A \bullet B = (A \oplus B) \ominus B \qquad (7)$$

Another two algorithms or operations, which are used in medical image segmentation [14] and related to mathematical morphology, top-hat and watershed transformations. The top-hat transformation has enhancement effect which is become estimating the local background by a morphology opening operation, and then subtract it from the original image resulting and this operation have a good effect on enhancing vessels.
The Top-hat of image A by structuring element B as shown in rule 8:

$$Top\_hat\ (A) = A - (A \circ B) \qquad (8)$$

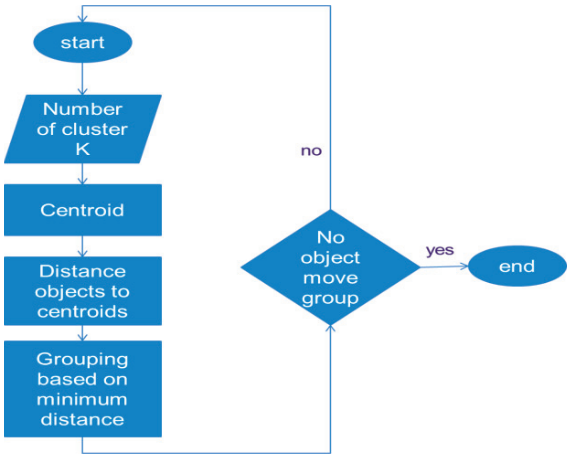

Fig. 1. Flow chart for K-Means algorithm.

3.2 K-means clustering algorithm

K-Means algorithm is categorized as an unsupervised clustering algorithm [15],[16]. Its methodology works on classifying the input data points into more than one class based on their distance from each other and from the centroid point which changes on each iteration figure 1 shows the flow chart of k-means algorithm which is relatively efficient and applicable. The algorithm deal with the data features as it form a vector space, and tries to find natural clustering in them. All points are iteratively clustered around centroids μ_i $\forall_i$=1......k which is obtained by minimizing the objective in rule 9:

$$V = \sum_{i=1}^{k} \sum_{x_j \epsilon s_i} (X_j - \mu_i)^2 \qquad (9)$$

K denoted to the number of clusters to be founded S_i , i = 1, 2,…. , k and $\mu_i$is mean point of all the points $x_i \in S_i$ or centroid, steps of the algorithm as follows:
1. Compute the histogram (intensity distribution) of the intensities.
2. The centroids are initialized with k random intensities.
3. The following steps are repeated until there are no more any changes on the cluster labels of the image.
4. Assign the points to the clusters depending on their distances from the centroid intensities as shown in rule 10.

$$C^{(i)} := arg\ min_j ||x^{(i)} - \mu_j||^2 \qquad (10)$$

5. For each of the clusters, the new centroid is computed as shown in rule 11.

$$\mu_i = \frac{\sum_{i=1}^{m} 1\{C_{(i)}=j\} x^{(i)}}{\sum_{i=1}^{m} 1\{C_{(i)}=j\}} \tag{11}$$

where i is the iterates over the all the intensities, j iterates over all the centroids and μ_i are the centroid intensities.

4. The Proposed System

The proposed segmentation system consists of two main phases; namely **mathematics morphology** as pre-processing phase, **Classification** phase. Figure 2 describes the general structure of the proposed approach.

For our approach we use the DRIVE (Digital Retinal Images for Vessel Extraction) [17] database. It is available and public database, containing 40 color funds digital images about population having subjects ranging between 31 and 86 years old. These digital images were taken by a Canon CR5 non-mydriatic 3CCD camera at 45 field of view (FOV). Each image is 768 * 584 pixels. The database contains [7] two main sets, test and training both of each containing 20 digital images. Three observers, the first and second author and a computer science student manually segmented a number of images. All observers were trained by an experienced ophthalmologist (the last author). The first observer segmented 14 images of the train set while the second observer segmented the other 6 images. The test set was segmented twice resulting in a set X and Y. Set X was segmented by both the first and second observer (13 and 7 images respectively) while set Y was completely segmented by the third observer. The performance of the vessel segmentation algorithms is measured on the test set. In set X the observers marked 577,649 pixels as vessel and 3,960,494 as background (12.7 % vessel). In set Y 556,532 pixels are marked as vessel and 3,981,611 as background (12.3 % vessel).

4.1 Mathematics Morphology Pre-processing phase

We use mathematical morphology process for smoothing and removing any noise. The important thing to get effective results on morphological processing is to select the appropriate structuring element. So depending on the features of vessels we select linear structuring element [2] which is proper to the line type property of vessels. It takes into account that when we perform opening operation with linear structure element which is longer than the vessels width, a vessel or some parts of it will be removed. In contrast there will not be any change with vessel if the vessel and the structuring element have parallel directions. So in this paper, we obtain the maximum response by convolving the digital image with linear structure element at various directions.

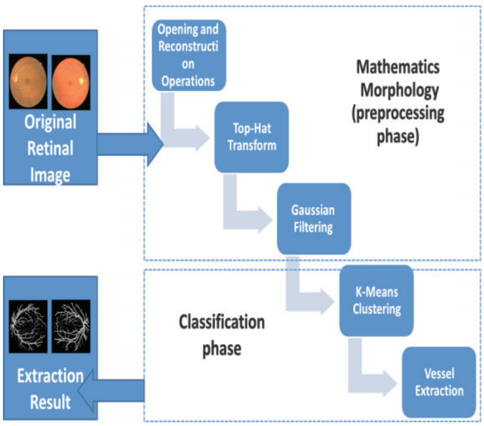

Fig. 2. Architecture of the proposed segmentation approach.

To extract larger vessels, we select structuring elements with length near to the diameter value of the largest vessels. In our experiments, in order to save the time spent on the segmentation, each structuring element is 7 pixels long and 1 pixel in width.

Step1. we apply opening operation γ_L[2] which is a sequence of two operations ;erosion ε_L followed by dilation δ_L on the original image I_0.The opened image I is obtained by calculating the maximum response of 12 directions, then reconstruction operation $\gamma_{I_0}^{rec}$ is applied on the opened image I to obtain the smoothed image I_s.

$$\gamma_L = \delta_L\big(\varepsilon_L(M)\big), \quad (12)$$

$$I = max_i = 0, \ldots\ldots, 12 \left\{\gamma_{L_i}(I_0)\right\}, \quad (13)$$

$$I_s = \gamma_{I_0}^{rec}(I), \quad (14)$$

Here

$$\varepsilon_L = min_{M+L(M)}(I_0(M)) \quad (15)$$

$$\delta_L = max_{M+L(M)}(I_0(M)) \quad (16)$$

Step2. We apply the Top-Hat transform to the result of previous step (smoothed image) at 12 directions, and then sum up the computational results of the 12 directions and by this method , the gray difference between the vessels and the background are increased.

$$I_{Top} = \sum_{i=1}^{12}\left(I_s - \gamma_{L_i}(I_0)\right), \quad (17)$$

Step3. We apply Gaussian filter with 7 pixels in width on the output of the previous result to generate more smoothed image as figure 3 shows the result smoothed image after mathematics morphology preprocessing step :

$$I_G = Gaussian_{\sigma=\frac{7}{4}}^{width=7}\left(I_{Top}\right), \quad (18)$$

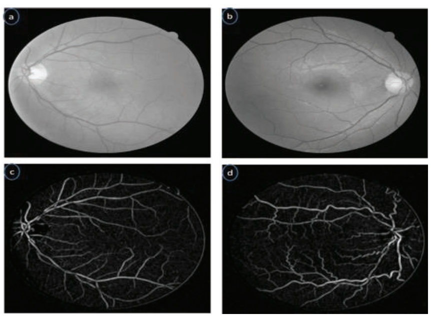

Fig. 3. Smoothed result after morphological preprocessing of a retinal image: (a, b) samples of original image, (c, d) after morphological preprocessing.

4.2 Classification phase

After enhancing of the retinal vessels, the vessels are to be extracted from the image. However, exactly determining the position of a vessel segment is ambiguous manner in the image because of the physics of the image-generation process, and it is taken into account the individual characteristics of the imaging system and the noise, so for image segmentation process, we need a powerful tool to handle this difficulties. We apply the K-means clustering in our methodology [18]; we aim to minimize variance within-group by portioning method for grouping objects. This method works as follows:

Step1. Two class centres are initialized randomly; representing as initial group centroids.
Step2. The value of histogram bin value distance between each image pixel and class centroids is calculated; each image pixel is assigned to its nearest class centroid.
Step3. The mean histogram bin value of the same group is calculated and assigned as the new position of centroid.
Step4. Step2 and step3 are repeated till the value of centroids changes.

5. Experimental Results

For the vessel segmentation approach, our algorithm was tested on the DRIVE public dataset with a total of 40 images divided into test and training sets, each containing 20 images of normal and abnormal cases with different ages ranging from 31 to 86 years old. The performance of our approach is tested and validated against a number of alternative approaches.
It is well known that we use some parameters to facilitate the comparison in performance and accuracy, these parameters such as the true positive rate (TPR), the false positive rate (FPR), the accuracy rate (ACC), sensitivity and specificity. The true positive rate (TPR) expresses the fraction of pixels correctly classified as vessel pixels. The false positive rate (FPR) expresses the fraction of pixels erroneously classified as vessel pixels. The sum of this true positive (pixels which is correctly classified as vessel) and the true negative (pixels which is correctly classified as non-vessels and it is actually non vessel points) divided by the total number of pixel in the digital images is called accuracy [19]. Sensitivity (SN) is how the algorithm is able to detect the vessel pixels. Specificity (SP) is how the algorithm is able to detect non-vessel pixels, table 1 shows the performance measures equations used by retinal vessel segmentation algorithms.

Table 1 Performance measure for retinal vessel segmentation.

Measure	Description
TPR	TP/vessel pixel count
FPR	FP/non-vessel pixel count
Specificity(SP)	TN/(TN+FP)
Sensitivity(SN)	TP/(TP+FN)
Accuracy(Acc)	(TP+TN)/FOV pixel count

Figure 4 shows the segmented images and the manually labeled images for the DRIVE datasets and, table 2 shows our approach results accuracy.

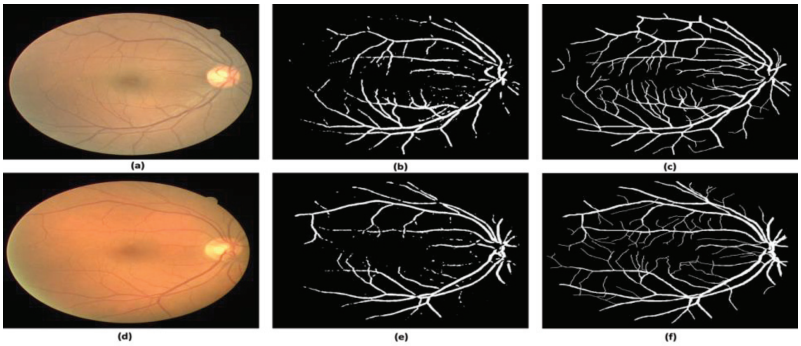

Fig. 4. The DRIVE dataset: a) and d) retinal images, b) and e) our segmentation results, and c) and e) manually labeled results system.

Table 2 Accuracy, sensitivity and specificity for our retinal vessel segmentation results.

Image	Accuracy	Sensitivity	specificity
1	0.96092	0.86007	0.97571
2	0.9531	0.87200	0.98813
3	0.98310	0.72548	0.97985
4	0.96145	0.85491	0.94905
5	0.94058	0.86150	0.94479
6	0.94921	0.71827	0.96796
7	0.95244	0.83179	0.96029
8	0.94985	0.82304	0.95992
9	0.95605	0.80920	0.97625
10	0.95242	0.73576	0.96760
11	0.96248	0.77864	0.97032
12	0.96637	0.87322	0.97011
13	0.97716	0.77607	0.97056
14	0.92633	0.81330	0.93914
15	0.95724	0.82881	0.96645
16	0.97263	0.84342	0.96065
17	0.95427	0.80998	0.96467
18	0.98937	0.73527	0.96693
19	0.94843	0.88259	0.97602
20	0.95733	0.70240	0.98003

The performance of our approach on DRIVE dataset is compared with alternative approaches: Martinez-Perez et al [19], Perez et al,Anzalone et al. [21], Vlachos and Dermatas. [22], Fraz, Rudnicka and Barman. [5], Yin and Bourennane. [6], Roychowdhury, Koozekanani and Parhi. [7] and Marin. [8]. Table 3 shows the performance of our approach against the above approaches on DRIVE dataset.

Table 3 Performance comparison on the DRIVE dataset

Approach	Sensitivity	Specificity	Accuracy
Martinez-Perez et al. [19]	0.7246	0.9655	0.9344
Perez et al. [20]	0.660	0.9612	0.9220
Anzalone et al. [21]	-	-	0.9419
Vlachos and Dermatas. [22]	0.747	0.955	0.929
Fraz, Rudnicka and Barman. [5]	0.74	0.98	0.96
Yin and Bourennane. [6]	0.7248	0.9666	-
Roychowdhury, Koozekanani and Parhi. [7]	-	-	0.952
Marin. [8]	0.7067	0.9801	0.9452,
Our approach	0.8799	0.9799	0.9625

The proposed approach achieves very good accuracy comparing with the approaches which implement morphological processing and with increasing of dataset images, improving in accuracy noticed with low rate of misclassification.

Figure 5 shows the true positive rates of the proposed approach with the second specialist's segmentations. Based on these results, we can notice that our method produce true positive rates near to the results of manual segmentation. However, the false positive rates of our method are less than those of the first and second specialist. The results shown here demonstrate that our method produce comparable results to the ground truth, which proves that the proposed method is effective, and have high efficiency rate.

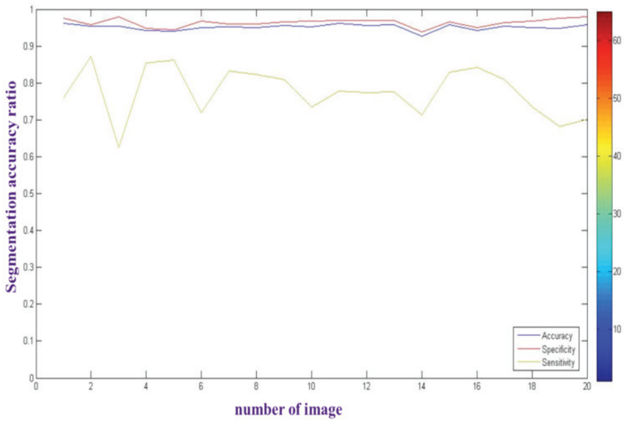

Fig. 5. Accuracy ratio of extraction results.

6. Conclusions and Future Work

In this paper, an automatic approach of vessel segmentation is presented. Mathematical morphology is applied as pre-processing phase with K-means clustering. Mathematical morphology firstly employed to enhance and smooth the digital retinal images and to suppress the background information. Then, the K-means clustering is applied to segment the vessels. And finally the blood vessels are extracted. Our results which obtained from the proposed method are compared with the standard segmentation methods. It achieves quantitative and qualitative results on normal and abnormal retinal images. Our results shows that the proposed system produce identical results as the ground truth and have a high accuracy ratio and low misclassification ratio comparing with the manual extraction, we aim to perform more efficient methodologies and improve in time complexity.

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