Optic Disc Segmentation Based on Independent Component Analysis and K-Means Clustering

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Abstract: The determination of the Optic Disc (OD) boundary is a fundamental step in the analysis of digital Diabetic Retinopathy (DR) systems. The novel method for automatically locate the Optic Disc (OD) is proposed in this paper. The proposed algorithm is mainly based on the K-means clustering and Independent Component Analysis (ICA). Unlike RGB color space, where R, G and B components are correlated, in the new ICA color space three components are statistically independent and uncorrelated. Prior to the Optic Disc segmentation the blood vessels are extracted and removed by local entropy thresholding and inpainting methods. The proposed method has been tested on a public datasets STARE and DRIVE with accuracy of 94.3% and 100%.

Keywords: Diabetic Retinopathy (DR), Independent Component Analysis (ICA) and K-Means Clustering.

1. INTRODUCTION

Retina is the innermost layer of the eye which can be visualized using adequate apparatus such as fundus camera. Fundus photography is the preferred medium for large scale screening [17]. Patients with diabetes are more likely to develop eye problems such as cataracts and glaucoma, but the disease’s affect on the retina is the main threat to vision [24]. OD detection is a key preprocessing component in many algorithms designed for the automatic extraction of retinal anatomical structures and lesions thus, reliable and efficient OD localization is significant tasks in ophthalmic image processing.

Figure 1 shows a healthy retinal image including main retinal features i.e. optic nerve, blood vessels and macula. The shape, color and size of optic disc help in localization and detection.

In the literature, OD detection can be classified into several groups. The first group uses properties of the OD such as high pixel intensity and its oval shape. Morphology [25] is also used where the OD center is the center of the brightest connected object found by thresholding an intensity image. Other authors have proposed shape-based approaches; e.g., Fleming et al. [1] deploy a Generalized Hough transform to detect the circular shape of the OD; Osareh et al. [2] use an automatically initialized snake to detect the OD boundary. Rajput, Yogesh M., et al. [22] use SURF (Speed Up Robust Features) to identify the optic disc. Vessel-based methods depend mainly upon extracting and analyzing the structure of the retinal vessels and defining the location of the OD as the point where all the retinal vessels radiate.

In Hoover and Goldbaum [4], Fernando C. Monteiro and Vasco Cadavez [18] use Earth Mover’s Distance (EMD) template matching method to detect OD. Retinal images need to be preprocessed before the OD detection. Several other works on the detection of retinal vessels have used the green channel only; Instead of using green channel brightness component of the CIE-Lab space to convert the RGB to grey-scale is proposed in [18]. Morales, Sandra, et al. [19] achieved greyscale image using Principle Component Analysis (PCA).

The method proposed in this paper is based on the ICA and K-means clustering. The main steps of the proposed method are following: First input RGB fundus image is applied to pre-processing step. In the pre-processing step the Independent Component Analysis (ICA) transforms the RGB image into the grey scale image [26]. RGB to ICA color space is a linear and reversible color space transform that gives three new coordinate axes where the projected data is as much as statistically independent as possible, and therefore highly uncorrelated. Then the blood vessels are extracted by applying local entropy thresholding method [10] and the extracted blood vessels are removed through inpainting [8] technique to make the segmentation process very easier. Next the optic disc is segmented by applying k-means clustering algorithm to the in-painted image. Finally in post-processing step the optic disc region is estimated using circular approximation method [3]. The block diagram of the proposed method is shown in figure 4.
The rest of the paper is organized as follows: In section II theoretical background of the proposed algorithm. In section III proposed algorithm. In section IV experimental results and comparison with other methods, finally in section V conclusion and future works.

2. THEORETICAL BACKGROUND:

1. ICA:

Overview of the independent component analysis as follows [6].

The basic ICA model is,

Consider we observe \( y \) random variables

\[ x_l = a_{l1} y_1 + a_{l2} y_2 + \ldots + a_{ln} y_n, \quad \text{for all} \ l = 1, \ldots, n \]

Where, \( a_{lj}, l,j = 1, \ldots, n \) are some real coefficients, by definition, the \( s_l \) are statistically mutually independent.

In the vector field,

Let us denote by \( x \) the random vector whose elements are the mixtures \( x_1, x_2, \ldots, x_n \) and likewise by \( s \) the random vector with elements \( s_1, s_2, \ldots, s_n \). Let us denote \( A \) the matrix with elements \( a_{ij} \).

Using this vector-matrix notation, the mixing model is written as

\[ x = As \quad (1) \]

Generally, random variables \( y_1, y_2, \ldots, y_n \) are said to be independent if the information on the value of \( y_l \) does not give any information on the value of \( y_i \) for \( i \neq l \).

Technically, independence can be defined by the probability densities. Let us denote by \( p(y_1, y_2, \ldots, y_n) \) the joint probability density function (pdf) of the \( y_l \), and by \( p_i(y_l) \) the marginal pdf of \( y_l \), i.e., the pdf of \( y_l \) when it is considered alone. Then we say the \( y_l \) are independent if and only if joint pdf is factorizable in the following way:

\[ p(y_1, y_2, \ldots, y_n) = p_1(y_1) p_2(y_2) \ldots p_n(y_n) \]

2. Matched Filter:

The concept of matched filter detection is used to detect the piecewise linear segments of blood vessels in the retinal images. Blood vessels usually have poor local contrast. The matched filter kernel is designed to convolve the image in order to enhance the blood vessel. The matched filter kernel is expressed as,

\[ f(x, y) = -\exp \left(-\frac{x^2}{2\sigma^2}\right), \quad \text{for} \ |y| \leq \frac{L}{2} \quad (2) \]

Where \( L \) is the length of the segment for which the vessel is assumed to have a fixed orientation.

3. Local Entropy Thresholding:

In order to extract the vessels, the image is processed by a proper thresholding scheme. An efficient entropy based thresholding algorithm, which takes into account the spatial distribution of the grey levels, is used because image pixel intensities are not independent of each other. The entropy thresholding method described in [10] which can preserve the spatial structures in the binarized image.

The co-occurrence matrix of the image \( I \) is an \( P \times Q \) dimensional matrix \( T = [t_{ij}]_{P \times Q} \) that gives an idea about the transition of intensities between adjacent pixels, indicating spatial structural information of an image. Depending upon the ways in which the gray level \( l \) follows gray level \( j \), different definitions of co-occurrence matrix are possible. Here, we made the co-occurrence matrix asymmetric by considering the horizontally right and vertically lower transitions. Thus, \( t_{ij} \) is defined as follows:

\[ t_{ij} = \sum_{l=1}^{P} \sum_{k=1}^{Q} t_{l+1} \sum_{l=1}^{P} \sum_{k=1}^{Q} t_{l+1,k} \]

Where,

\[ \delta = 1 \quad \text{If} \quad \{f(l, k) = l \quad \text{and} \quad f(l, k + 1) = j\} \]

\[ \delta = 0 \quad \text{Otherwise} \]

The probability of co-occurrence \( p_{ij} \) of gray levels \( l \) and \( j \) can therefore be written as

\[ p_{ij} = \frac{t_{ij}}{\sum_{l \neq j} \sum_{l \neq j} t_{ij}} \quad (4) \]
If \( s, 0 \leq s \leq L - 1 \) is a threshold. Then \( s \) can partition the co-occurrence matrix into 4 quadrants, namely \( A, B, C, \) and \( D \) (figure 3).

\[
\begin{array}{c|c|c|c|c}
0 & s & \vdots & L-1 \\
\hline
A & B & \vdots & D \\
\hline
s & \vdots & \ddots & \vdots \\
\hline
L-1 & \vdots & \ddots & D
\end{array}
\]

Figure 3 Quadrants of co-occurrence matrix [20].

Let us define the following quantities:

\[
P_A = \sum_{i=0}^{s} \sum_{j=0}^{s} P_{ij} \\
(5)
\]

\[
P_C = \sum_{i=s+1}^{l-1} \sum_{j=s+1}^{l-1} P_{ij} \\
(6)
\]

Normalizing the probabilities within each individual quadrant, such that the sum of the probabilities of each quadrant equals one, we get the following cell probabilities for different quadrants:

\[
P_{ij}^A = \frac{P_{ij}}{P_A} = \frac{t_{ij}/(\sum_{j=0}^{s} t_{ij})}{\sum_{i=0}^{s} \sum_{j=0}^{s} t_{ij}}
\]

For \( 0 \leq i \leq s, 0 \leq j \leq s \)

\[
P_{ij}^C = \frac{P_{ij}}{P_C} = \frac{t_{ij}/(\sum_{j=s+1}^{l-1} t_{ij})}{\sum_{i=s+1}^{l-1} \sum_{j=s+1}^{l-1} t_{ij}}
\]

For \( s + 1 \leq i \leq L - 1, \) \( s + 1 \leq j \leq L - 1 \)

The second-order entropy of the object can be defined as

\[
H_A^{(2)}(s) = -\frac{1}{2} \sum_{i=0}^{s} \sum_{j=0}^{s} P_{ij}^A \log_2 P_{ij}^A
\]

Similarly, the second-order entropy of the background can be written as

\[
H_C^{(2)}(s) = -\frac{1}{2} \sum_{i=s+1}^{l-1} \sum_{j=s+1}^{l-1} P_{ij}^C \log_2 P_{ij}^C
\]

Hence, the total second-order local entropy of the object and the background can be written as

\[
H^{(2)}(s) = H_A^{(2)}(s) + H_C^{(2)}(s)
\]

The gray level corresponding to the maximum of \( H^{(2)}(s) \) gives the optimal threshold for object-background classification.

4. In-painting:

In-Painting is an efficient algorithm to restore the damaged digital photograph or scene. In-painting algorithms are used in many applications to remove the selected region from the digital photograph [8]. Let a binary image \( \Omega(x) \) stands for the region to be inpainted and \( \partial \Omega \) for its boundary. For each \( x \) pixel, the in-painted pixel value is calculated as

\[
P(x) = \frac{\sum_{k=1}^{5} P_k(x)}{\sum_{k=1}^{5} 1}
\]

Where \( P_k \) denotes the pixel values in \( 5 \times 5 \) neighborhood of the pixel under consideration, \( n \) is the number of neighboring pixels, and \( l \) is the distance between the pixel \( x \) and each neighboring pixel. So that the in-painted image \( y(x) \) of a gray image \( f(x) \) is

\[
y(x) = \begin{cases} 
  f(x), & \text{if } \partial \Omega(x) = 0 \\
  P(x), & \text{if } \partial \Omega(x) = 255 
\end{cases}
\]

After filling \( \partial \Omega \) with the computed values, the \( \partial \Omega \)-pixels are removing from \( \Omega \) and \( \partial \Omega \) is recalculated. The process is repeated until the mask is empty and all pixels have been filled.

Figure 5 Preprocessing Results: a) RGB Image, b) ICA First Component, c) Extracted Blood Vessels, d) Vessel Mask to be in-painted and e) In-painted Image

Figure 6 Segmentation Results: a) In-painted image, b) Segmented Optic disc using k-means, c) Thresholding, d) Optic Disc Boundary and e) Circular Approximation of OD

5. K-Means Clustering:

K-means clustering [14] is one of the simplest unsupervised learning algorithm that solves the well known clustering problem. Given set of observations \( X_1, X_2, \ldots, X_N \) where each observation is a \( d \) - dimensional real vector, k-means clustering aims to
partition the \( n \) observations into \( k \) sets (\( k \leq n \)) so that neighboring pixels have a high probability of falling into the same cluster. The objective function of \( j \) is an indication of the distance of the \( n \) data points from their respective cluster centers.

The step by step procedure of the \( k \)-means clustering algorithm as follows,

1. Place \( k \) points into the space represented by the objects that are being clustered. These points represent initial group centroids.
2. Assign each object to the group that has the closest centroid.
3. When all objects have been assigned, recalculate the positions of the \( k \) centroids.
4. Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated.

3. PROPOSED ALGORITHM:

The adaptive color space transform is based on the independent component analysis to a RGB color image [26] [27]. The each of the three RGB channels has a mixture of three independent components, which might not be necessarily true, but three are most independent as possible. Consider RGB channel as three vectors and apply independent component analysis algorithm FastICA [7] as a result we get a mixing matrix \( W \), which will define color space transform matrix for a particular image, the separation matrix, and its inverse \( A \) can be further used to perform the color space transform back for the same image. Figure 2 shows the comparison of the various color space transform applied to the retinal image. Unlike RGB color space, where R, G and B components are correlated, the new ICA color space method derives three components IC1, IC2 and IC3 are statistically independent and uncorrelated. The proposed ICA color space transform outperforms the PCA color space [19]. The next important pre processing step is to extract the blood vessels in the retinal image. For detect the blood vessels the green component of the retinal image is used. The blood vessels are first detected by method proposed in [10]. The matched filter is applied to the green component of the retinal image to enhance the blood vessels further. In order to extract the vessel segments from the background image the entropy thresholding is applied to perfectly extract the blood vessels. The detected blood vessels are used as a inpainted mask and the blood vessels in the image are removed by applying in-painting algorithm. Figure 5 shows the results of preprocessing steps. This process leads to ease of segmentation process. Once the blood vessels are removed from the retinal image segmentation of the optic disc is done by applying \( k \)-means clustering which classify pixels in an extracted feature space. Finally, these clusters are grouped using segmentation map function with a \( k \) value equal to 3. The \( K \)-Means can then be used to segment the image into three clusters - corresponding to two scripts and background respectively. For each additional script, one more cluster is added. Here, each feature is assigned a different weight, which is calculated based on the feature importance as described in the previous Section. Once the image has been segmented using the \( K \)-Means algorithm, the clustering can be improved by assuming that neighboring pixels have a high probability of falling into the same cluster. The detected optic disc boundary is approximated by circular approximation presented in [3] [16]. Figure 6 shows the results of segmentation and circular approximation result of the optic disc.

4. RESULTS AND COMPARISON:

The validation of the proposed method is carried out by two databases DRIVE [15] and STARE [5]. In STARE database we have tested with 53 images resolution of 1900X1600 pixels and in DRIVE database 40 images resolution of 565X584 pixels, 33 do not show any sign of diabetic retinopathy and seven show signs of mild early diabetic retinopathy. The detected optic disc of some of the STARE database images as shown in figure 7. The performance of the proposed system has been evaluated in based on Accuracy (A), Dice co-efficient (S) [11] and Jaccard co-efficient (JC). Accuracy is calculated by total number of successful detection divided by total number of failed detection.

![Figure 7 Results of Detected Optic Disc from STARE database](image)

<table>
<thead>
<tr>
<th>Database</th>
<th>Total Images</th>
<th>Successful Detection</th>
<th>Failure Detection</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>STARE</td>
<td>53</td>
<td>50</td>
<td>3</td>
<td>94.3%</td>
</tr>
<tr>
<td>DRIVE</td>
<td>40</td>
<td>40</td>
<td>0</td>
<td>100%</td>
</tr>
</tbody>
</table>

a) Jaccard Co-efficient:
Jaccard co-efficient measures the similarity between two sample sets, and is defined as the size of the intersection divided by the size of the union of the sample sets

\[ J^C = \frac{|A \cap G|}{|A \cup G|} \]  

The jaccard distance is obtained by subtracting the Jaccard coefficient from 1.

Table 2 Results (Average) obtained by proposed method using DRIVE and STARE databases. Jaccard (JC) and Dice (S)

<table>
<thead>
<tr>
<th></th>
<th>DRIVE</th>
<th>STARE</th>
</tr>
</thead>
<tbody>
<tr>
<td>JC</td>
<td>0.7962</td>
<td>0.7090</td>
</tr>
<tr>
<td>S</td>
<td>0.8865</td>
<td>0.8297</td>
</tr>
</tbody>
</table>

b) Dice co-efficient:
The Dice coefficient (S) is one of a number of measures of the extent of spatial overlap between two binary images. It is commonly used in reporting performance of segmentation and gives more weighting to instances where the two images agree. Its values range between 0 (no overlap) and 1 (perfect agreement).

\[ S = \frac{2(|A \cap G|)}{|A \cup G| + |G \cup A|} \]  

Table 1 shows the accuracy of the proposed method for DRIVE and STARE database. In DRIVE database our proposed method has achieved 100% of accuracy. In the evaluation of jaccard and dice co-efficient our method outperforms method proposed by [19]. Table 2 shows jaccard (JC) and dice (S) co-efficient values for both DRIVE and STARE databases. In pre processing step our proposed independent component analysis approach gives the better result than previously proposed PCA and usual Red component segmentation. Table 3 shows the performance of proposed method with color space conversion using Principle Component Analysis (PCA).

Title 3 Comparison between the color space transforms of ICA (proposed) and PCA on DRIVE database

<table>
<thead>
<tr>
<th></th>
<th>ICA(Proposed)</th>
<th>PCA(Sandra et al)</th>
</tr>
</thead>
<tbody>
<tr>
<td>JC</td>
<td>0.7962</td>
<td>0.7163</td>
</tr>
<tr>
<td>S</td>
<td>0.8865</td>
<td>0.8169</td>
</tr>
</tbody>
</table>

5. CONCLUSION AND FUTURE WORK:
A new approach of Optic Disc (OD) detection algorithm has been presented in this paper. First it is focused mainly on the RGB to grey scale image conversion based on Independent Component Analysis (ICA) which gives three new coordinate axes where the projected data is as much as statistically independent as possible, and therefore highly uncorrelated. Secondly the matched filter based entropy thresholding is used to extract the blood vessels to make the in-painting mask. Prior to segmentation the blood vessels are removed by applying in-painting method. To achieve the accurate segmentation k-means clustering is used. Finally the proposed method performance is validated using two different databases. The goal of the proposed method is to detect the early stages of fundus diseases. In future to diagnose glaucoma disease in early stages cup-to-disc ratio will be measured by detecting the optic cup inside optic disc.

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References


