

## **Microaneurysm Detection Using singular spectrum analysis**

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**Abstract:** *Diabetic retinopathy is one of the leading disabling diseases in eye, it will be a leading causes of preventable blindness in the world. Early diagnosis of diabetic retinopathy enables timely treatments. In order to achieve this a major concern will have to be invested into automated screening programs. For automated screening programs of diabetic retinopathy, image processing and analysis algorithms have to be developed. Candidate objects are first located by applying a dark object filtering process. Then singular spectrum analysis process detects the microaneurysm. A set of statistical features of those profiles is then extracted and check shape of the candidate profile, compactness, area etc. By comparing singular spectrum analysis image and feature extraction image using general classification, get the correct position of microaneurysm.also The growth of the disease can be find out by singular spectrum analysis.*

**Keywords:** *image processing, microaneurysms, multilayered dark object filtering, singular spectrum analysis*

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### **I. Introduction**

Diabetes is one of the most widespread diseases in the world. The World Health Organization (WHO) reported that there are 347 million people suffering from diabetes and also record says this disease will be the leading cause of death in 2030 [1]. One possible complication of the disease is diabetic retinopathy, Diabetic retinopathy (DR) is one of the leading disabling diseases effect in eye, and one of the leading causes of blindness in the world [2]. It occurs when diabetes damages the tiny blood vessels inside the retina. There are mainly two types of diabetic retinopathy called non-proliferate diabetes retinopathy (NPDR) and proliferate diabetes retinopathy (PDR). Non proliferative retinopathy is the early stage of diabetic retinopathy and can be viewed only by high resolution fundus photography. Proliferative retinopathy is the later stage of diabetic retinopathy. Here dark red blood spots appear in the eye due to the bursting of fragile blood vessels of the retina. Early diagnosis through regular screening will prevent the burden of the disease [3]. The first significant symptoms of diabetic retinopathy is small reddish dot in the retina, called microaneurysms. In the early stages of microaneurysms detection can be crucial.

### **II. Diabetic Retinopathy**

Diabetes is a well known disease that may cause abnormalities in the retina (diabetic retinopathy) and nervous system (diabetic neuropathy). Also diabetes can make a major risk for cardiovascular diseases. Diabetic retinopathy is a microvascular complication caused by diabetes which can lead to blindness in the working age population[4]. blood vessels providing blood supply to the retina when blood vesssels gradually weakens due to diabetes, it can be swelled and blocked.The disordered and weak small blood vessels are not able to maintain the right blood supply, they can be burst,thereby exudate and blood can leak out to the vitreous part. The blood flown to vitreous part obstructs the path of light to the retina, thereby worsens vision.

In Some times fluid is flows below the retina, then it can move from back wall of the eye, such condition distorts vision. In serious cases the retina and blood vessels are detach, which causes blindness. In early stages of diabetic retinopathy like microaneurysms have typically no visible signs, but the severity and number of abnormalities increase during that time. The early stage of Diabetic retinopathy typically starts with small changes in retinal capillaries. The first detectable abnormality is microaneurysms, which results local enlargements of the retinal capillaries. The ruptured microaneurysms can cause hemorrhages, that appear as flame or blot like structure. The small circle shaped swelled vessels are called microaneurysms (MA)[5], which can be detected in early stages of the diabetic retinopathy.



**Fig 1** image of normal retina



**Fig 2** image of diabetic retinopathy

### III. Proposed Method

The proposed method is performed on the green channel of retinal fundus image. The MAs, haemorrhages and vessels normally present the highest contrast against the surrounding background in green channel, so they appear as bright structures and get finer details [6]. The MA detection process is divided into mainly 4 steps: there are preprocessing, candidate extraction through multilayered dark object filtering, candidate cross section profile analysis based on SSA, feature extraction and classification. The details of these 4 stages are described in the following sections.

#### 3.1 IMAGE PREPROCESSING

Preprocessing is the common stage which attenuates the effect of the noise and retains the true information of MAs. The techniques performed on the green channel of RGB color image, the filtered image  $I_{gg}$  is caught by Gaussian filter. A Gaussian filter is applied to the green channel  $I_g$ ; it enhances the small and dark structures as shown in Figure 3 (b). Due to the noise, many tiny structures preserving those corresponding to MAs or vessels. The Gaussian filter with a particular size of width and variance removes these tiny structures. In this project, we apply width = 3; variance = 1 for the best result. Also, it can identify, when bright regions or lesions are close together, forming small gaps between them to be considered as MAs in the later stages of the processing [7]. In order to prevent these false positives (FPs), a shade correction method [8] is extended to remove any bright region from image  $I_{gg}$ .

a) First, estimate a background image  $I_{bg}$  (Figure 3 (c)) by applying a median filter with a particular background estimation range (35 x 35) to  $I_{gg}$ .

b) Obtain shade correction image  $I_{sc}$  by subtracting  $I_{bg}$  from  $I_{gg}$  (Figure 3 (d)). Any pixel in  $I_{sc}$  that has a positive value means, in  $I_{gg}$ , the corresponding pixel has a higher intensity value than its neighbouring retinal background intensity. These pixels are used to locate bright regions in  $I_{gg}$ .

c) All bright pixels in Gaussian filtered image ( $I_{gg}$ ) indicated by shade correction image ( $I_{sc}$ ) are replaced by corresponding pixels value in  $I_{bg}$  resulting in an image  $I_{pp}$  (Figure 3 (e)). This process removes all the bright regions (including bright lesions) from the image  $I_{gg}$ ; it also removes the gaps among the bright lesions or regions cluster together causing to be considered as MAs. The pixels in  $I_{sc}$  with a zero or negative value are processed for candidate extraction in the next stage.

#### 3.2 MULTILAYERED DARK OBJECT FILTERING FOR EXTRACTION

Any object in the image showing MA-like characteristics then the candidate extraction process identifies such characteristics. These candidates will then be further analyzed or classified into MAs and non-MAs using filtering process. The method is able to extract isolated MAs away from other dark objects including vessels. However, when an MA is next to other dark objects, it was often not detected but considered as part of the neighboring objects. Calculate if its eight neighboring pixels have lower or the same intensity. Here the pixel is regarded to be a local maximum (in an inverted image), if the use of these local maxima made it easier to find out more MAs.

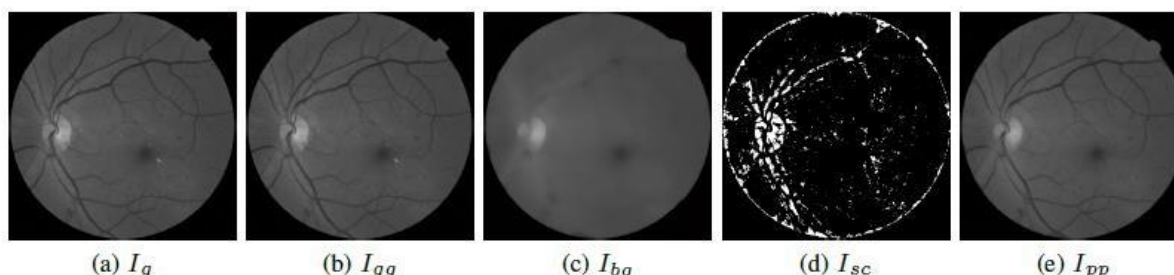


Fig.3. (a) The green channel of the fundus image. (b) The Gaussian filtered image of (a). (c) The estimated background image  $I_{bg}$ . (d) Shade correction image  $I_{sc}$  was accomplished by subtracting the median filtered image  $I_{bg}$  from  $I_{gg}$ . The white parts indicate bright regions (including bright lesions). (e) The preprocessed image  $I_{pp}$  (the bright pixels in  $I_{gg}$  indicated in  $I_{sc}$  are replaced by the values of corresponding pixels in  $I_{bg}$ ).

First histogram is applied, Histogram equalization automatically determines a transformation function that seeks to produce an image with uniform histogram. If background and image pixels have gray levels, they can be separated with a threshold value. The value 0 represent background and 1 represent object or aneurysm. Then This image is converted to binary. Binary image also have two values: 0 and 1. For segmentation of image, Binarisation is one of the important approaches. The gray scale image is converted into black (background) and white (aneurysm) image after binarisation. Lighter region is converted to white and the darker area will be transformed to black pixel, so only black and white pixel will be present. Then compare each pixel with its eight neighboring pixels. In the final step we get the image after vessel removal. This image has no boundary so in next step detect the outer side using edge detection method. Then calculate the area based on threshold value. Connected components that are less than threshold value, which produce another binary image  $BW3$ . This operation is known as an area opening operation, used to attain detection of microaneurysm. multilayered dark object filtering method reduce common interfering structures as MA candidates such as vessel crossings as well as many small background regions due to high local intensity variation. After preprocessing, all pixels with negative values or zero value in  $I_{sc}$  are regarded as initial positions to examine dark objects like vessels, dark lesions and noise in image  $I_{pp}$ .

Here the algorithm based on multilayered dark object filtering.the line 3 and 6 represent the connected neighbourhood strength is thresholded to ensure the pixels sufficiently darker than their background are chosen. threshold ( $\Delta$ )is denoted as  $\Delta = \mu + k\sigma$ , where  $\mu$  and  $\sigma$  are the mean and the standard deviation of the connected neighbourhood strengths of shade correction image  $I_{sc}$ . if a pixel O has N neighbouring pixels that have strength greater than  $\Delta$ , it will appear in candidate layers 1 through N. If all of its neighbouring pixels' strengths have higher values than  $\Delta$ , the current pixel will appear in all layers. On the contrary, if none its neighbours' strengths are higher than  $\Delta$ , this pixel cannot appear in any layer.

\_ A higher neighbouring pixels value means pixel O has more darker neighbours(N), the dark pixel itself is more likely in the middle of a dark object.

\_ A lower N means pixel O is more likely to be on the edge of a dark object.Any candidate object which have threshold value is grather than already mentioned threshold value is removed.

To determine a threshold  $\Delta = 100$ .This means any candidate object have threshold value greater than 100 ,remove that object and select only the object which have threshold value less than or equal to 100.

### 3.3 .EXTRACTION OF SSA BASED PROFILE

SSA [9] is able to decompose the profile series and then reconstruct them in order to enhance meaningful signals by remove the noise. The main advantage of SSA method is that the size of the generated Hankel matrix vary according to the expected number of underlying signal components and its diagonal elements are equal, while I n Principal Component Analysis (PCA) method ,this is fixed. Through SSA significantly better data decomposition into subspaces is achieved. After applying SSA, the key characteristics and differences between the candidate profiles of MAs and non-MAs are more significant. The SSA technique briefly described below. SSA generates a trajectory matrix X from the original series  $x_1$  by sliding a window of length L. The trajectory matrix is approximated using Singular Value Decomposition. The last step reconstructs the series from the approximated trajectory matrix. The SSA applications include smoothing, filtering, and trend

extraction. Two main steps of the basic singular spectrum analysis algorithm include decomposition and reconstruction.

### 3.3.1 Decomposition

The decomposition consists of embedding operation and singular value decomposition (SVD). The cross sectional intensity profile  $f$  with length  $N$  is mapped into an  $l \times k$  matrix by applying the embedding operation:

$$X = \begin{bmatrix} f_0 & f_1 & \dots & f_{k-1} \\ f_1 & f_2 & \dots & f_k \\ \vdots & \vdots & \ddots & \vdots \\ f_{l-1} & f_l & \dots & f_{N-1} \end{bmatrix}$$

where  $k = N-l+1$ ,  $l$  denotes the window length ( $1 \leq l \leq N$ ). The trajectory matrix  $X$  is a Hankel matrix which has equal elements for all the diagonals  $i + j = \text{constant}$ , where  $i$  and  $j$  are indices of rows and columns. In our implementation,  $l$  was empirically set to half of  $N$  ( $l = 10$ ). Then, the SVD of the trajectory matrix is created and represented as the sum of rank-one biorthogonal elementary matrices. Let  $Cx = XX^T$  and assume  $\lambda_1, \lambda_2, \dots, \lambda_l$  are the eigenvalues of the covariance matrix  $Cx$  in decreasing order ( $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_l \geq 0$ ) and denote the corresponding eigenvectors by  $U_1$  to  $U_l$ . In this method the matrix are multiply and store in a variance, take its eigen value for energy calculation. then sort the diagonal elements, sorted value sum are used to plot the singular spectrum.

### 3.3.2 Reconstruction

In this step, the elementary matrices are firstly divided into a number of groups and summed within each group. reconstruct the value based on singular spectrum using argupation component. argupation is the function to select which of the principal component that will not be used to reconstruct the series. for reconstruction we consider only part of total matrix. so we want to group the value based on minimum or maximum value of  $l$  and  $k$ . By using SSA we can decompose the original data into a set of principal components. The aim of this project to obtain the profiles of MA candidates without any noise. the smallest eigenvalues are regarded as noise and the largest eigenvalues belong to the signal subspace. After testing on many images, we observed that  $\lambda_1 \gg \lambda_2$ . Hence, chose the first eigenvector for reconstruction.

## 3.4 FEATURE EXTRACTION AND CLASSIFICATION

As compared to those works that focused on pure pixel intensity profiles, SSA generated profiles further highlight the candidate object information and minimize the impact from the noise. After observing SSA-based profiles, we found the shapes of MA profiles are more similar in all directions than those of non-MAs. In order to increase the difference between MAs and non-MAs, a dissimilarity score was assigned to each cross-section profile of a candidate object. A correlation coefficient formula is used to calculate the dissimilarity score between an estimated MA profile and each of the 12 scanning profiles  $f_r$ . A Gaussian function  $G$  is used to generate the estimated cross-section of MA which exhibits a Gaussian shape.

features are extracted from the profiles based on:

- 1) The mean and standard deviation of the peak widths of all cross-section profiles of the object.
- 2) The mean and standard deviation of the heights of decreasing slopes of all cross-section profiles of the object.
- 3) The mean and standard deviation of the heights of increasing slopes of all cross-section profiles of the object.
- 4) The compactness of an object that is, the distance from its  $j$ th edge point of slope (slope inc; slope dec) to the centroid of the profile and  $d$  is the mean of the distance from each edge point to the centroid. Here  $n$  is the total number of edge points.
- 5) The mean and standard deviation of the largest eigenvalues of all profiles.
- 6) The mean and standard deviation of the aspect ratio,  $r = \lambda_1 / \lambda_2$ .  $\lambda_1$  and  $\lambda_2$  are the respective values of the first and second largest eigenvalues of a profile. From these features we get microaneurysm region. Then compare the dark object filtered image and singular spectrum analysis based image for true microaneurysm region.

The classification of the candidate based on the comparison of detected microaneurysm, from multilayered dark object filtering process and feature extraction process.

#### **IV. Conclusion**

Proposed MA detection achieved a good sensitivity and specificity on a per image basis. This is especially meaningful when this method is integrated into a reliable automated system for detecting abnormality in digital fundus images. The proposed candidate filtering process is able to significantly reduce the number of non-MA candidates and sufficiently extract more candidates located close to the vasculature. We take the advantage of a basic SSA method to filter MA candidates' profiles.

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