

Retinal Hemorrhage Detection Using Feature Classification

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Abstract: Diabetic Retinopathy is a retinal disease because of high blood sugar. Early detection is necessary to maintain our vision. Small and large retinal hemorrhages can be detected using feature classification by extracting features from fundus images using filters bank outputs. Image level interpretation can be done by using difference of first and second order derivatives of Gaussian filters from green channel result. Finally a set of extracted features are selected with the help of filter approach and wrapper approach. k-NN classifier is used for final feature classification.

Keywords: Feature extraction, Hemorrhage, Feature selection, k-NN classifier.

1. Introduction

Diabetic Retinopathy is the most common cause of blindness among adults of age 20-74 years. Every year about 12,000 to 24,000 people loss their vision because of diabetics. High blood sugar level can damage and weaken tiny blood vessels in retina. This can result in various problems such as micro aneurysms, drusen, hard and soft exudates, cotton wool spots, hemorrhage etc. There are mainly two types of Hemorrhages, such as small and large hemorrhage [2]. Figure 1 shows hemorrhage affected retinal images which is our input images. Compared with anatomical structures ,such as fovea , blood vessels ,and optic disc ,the shape and appearance of hemorrhages may vary. Therefore early detection and regular treatment is necessary to maintain our vision.

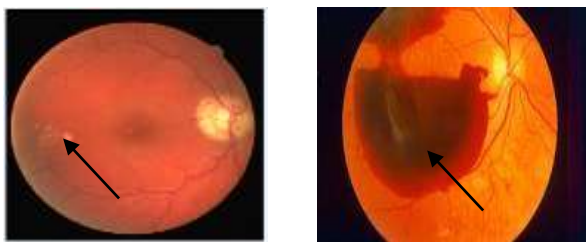


Fig.1 (a) Retinal image with small hemorrhage.(b) Large hemorrhage.

The two stages of Retinopathy are Non-Proliferative and Proliferative. Non-proliferative retinopathy is the early stage of diabetic retinopathy and can be viewed only through high resolution fundus images. Proliferative retinopathy is more advanced and severe but it is less common. Retinal hemorrhage detector using splat features can be used for detecting large and irregular hemorrhages.

Hemorrhage detection is basically consists of three catagories.

- (1)Pixel-Based Approach
- (2)Lesion-based approach
- (3)Image-based approach.

In pixel-based Approach ,it aimed for locating the hemorrhage on retina. Lesion-based approach use morphological operations to define lesions and count them. In Image-based approach, it detects whether the image consists of

hemorrhage or not. The size of lesions are not an important factor in the detection of hemorrhage on retina. Its mainly depends to the severity of disease that needs timely treatment. This paper proposes on detecting retinal abnormalities such as large and small hemorrhages using feature extraction and classification.

2. Proposed system

Retinal hemorrhage detection using feature classification consists of several steps. Figure 2 represents an overall idea on the work.

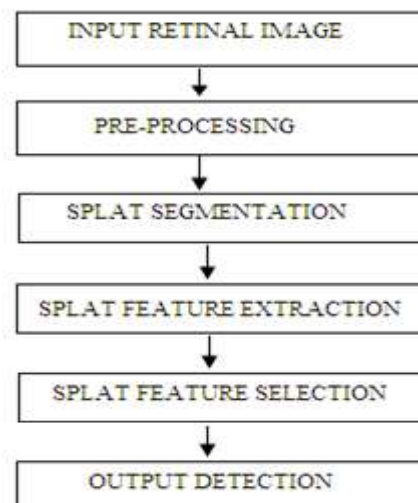


Fig.2 Block representation of proposed method

2.1 Input Retinal Images

Retinal images are the interior surface of eye that specifies opposite portion of lens which include retina, optic disc, macula, fovea and posterior pole. Retinal images can be examined and verify by ophthalmoscopy. Publically available images are used for the feature classification.

2.2 Pre-Processing

Pre-processing is the initial step in retinal hemorrhage detection. Initially input color image is converted into grey

scale image. This image is basically used for further feature extraction, selection, classification and for final detection. The retinal images may contain several noises. The noises are removed through pre-processing step.

2.3 Splat-Segmentation

Splat segmentation is used for partitioning the image into different segments based on color, intensity and spatial location. Splat is the part of pixel from same object or structure that shares similar color, intensity and spatial locations. Partitioned image into non-overlapping segments with similar intensity, which cover the entire image. Splat segmentation can be done by using watershed algorithm[3]. Computing gradient magnitude is the primary step in watershed algorithm. Aggregating the gradient magnitude of the contrast enhanced dark-bright opponency images at a scales for localization of contrast boundaries separating blood and retinal background is mainly because of variability in appearance of hemorrhages. Then maximum of these gradient is taken for performing watershed segmentation[4]. Gradient magnitude is computed by using the equation,

$$|\nabla I(x, y; m)| = \sqrt{I_x(x, y; m)^2 + I_y(x, y; m)^2} \quad (1)$$

$$= \sqrt{\left[\frac{\partial}{\partial x}(G_m * I(x, y))\right]^2 + \left[\frac{\partial}{\partial y}(G_m * I(x, y))\right]^2} \\ = \sqrt{\left[\frac{\partial G_m}{\partial x} * I(x, y)\right]^2 + \left[\frac{\partial G_m}{\partial y} * I(x, y)\right]^2} \quad (2)$$

Where * represents convolution and ∇ shows first order derivatives of Gaussian kernels. $m=m_1, m_2, \dots, m_n$ are the kernels of Gaussian operator. Instead of Gaussian operator, Sobel operator provides better results for detecting boundaries of fundus images. Figure 3 shows the gradient magnitude and watershed segmentation result. Then maximum of the gradient magnitude is also calculated.

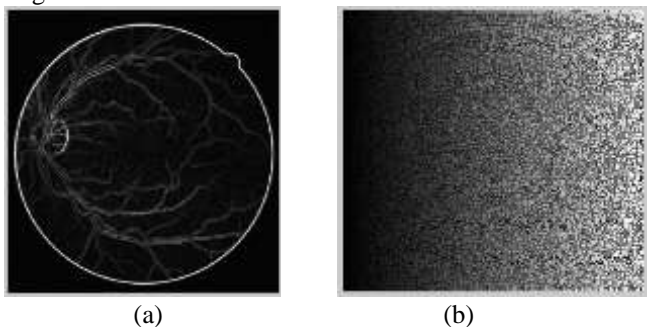


Fig 3. (a) Gradient magnitude using sobel operator.
(b) Watershed Result

2.4 Splat Feature Extraction

Transforming input data into a set of features are called feature extraction. Color within each splat is extracted in RGB color space[5]. To accommodate color variations across dataset, normalize each image according to the dominant pixel values at three color channels. To extract a set features, some filter banks are used. Mainly DoG filter, Gaussian filter bank, Schmid filter bank[7], Local texture filters are used. In DoG filter, it depends on σ and σ_0 values. Usually σ can be 1,2,4,8,16 and $\sigma_0=0.5$. In Gaussian filter bank it includes, First and second order derivatives which is applied to the green channel. Performing Gaussian difference image, which means, subtracting first and second order derivatives from green channel shows the hemorrhage affected locations[6].

In some cases image level interpretation for small hemorrhages is not easily possible. But in Gaussian difference image, it can easily locate large and small retinal hemorrhage. Figure 4

shows large and small retinal hemorrhage affected area on fundus images. A schmid filter bank consists of 13 rotationally invariant kernels. Texture features are extracted according to the statistics of Gray Level Co-occurrence Matrix (GLCM)[8] and tamura signatures[10]. In GLCM mainly contrast, correlation, energy and homogeneity is computed and in tamura signatures, mean, variance, skewness, kurtosis, entropy etc.. are calculated[11][12].

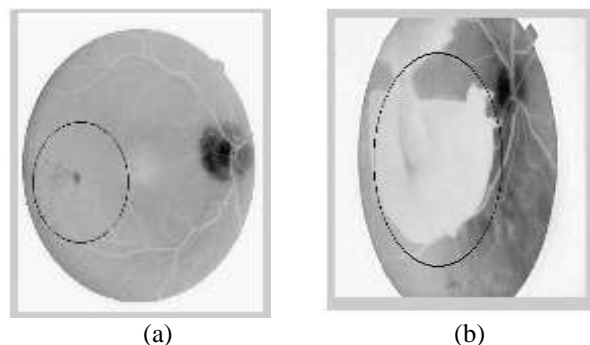


Fig 4. (a) Small Retinal hemorrhage affected fundus image.
(b) white portion inside small circle shows large hemorrhage.

2.5 Splat Feature Selection

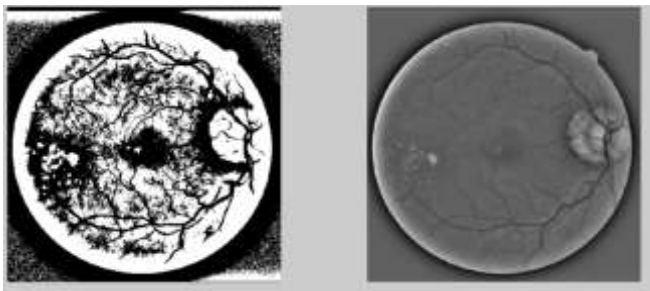
Feature selection means selecting a set extracted features for final classification. Feature selection includes eliminating irrelevant data's. It consisting of two steps- The filter approach and the wrapper approach. After selecting the individual needed features, Wrapper approach is used to select the different combinations of feature subset based on the interactions and to minimize the redundancy[1][13]

The available images are partitioned into training set and testing set. The training set are then grouped into two classes. Based on the available information's, the images are grouped into hemorrhages and non-hemorrhages. By taking interactions among features into account, a wrapper approach selects optimal combinations of relevant features with their redundancy minimized. Potential combinations are evaluated depending upon certain classification algorithms. A k-nearest neighbor (k-NN) classifier is used for this purpose.

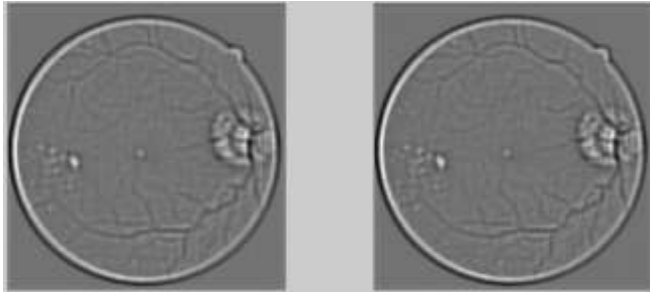
In pattern recognition, the k-Nearest Neighbors algorithm is a non-parametric method used for regression and classification. In both cases, the input consists of the k closest training examples in the feature space. Usually the output depends on whether k-NN is used for regression or classification. The input consists of the k closest training examples in the feature space. The KNN classifier is used to reduce the computational load. One of the major difficulty with the practical exploitation of the power of the K-NN approach is that, if there is no time required to estimate parameters from the training data, the time to find the nearest neighbors in a large training set can be prohibitive[14][15].

3. Results

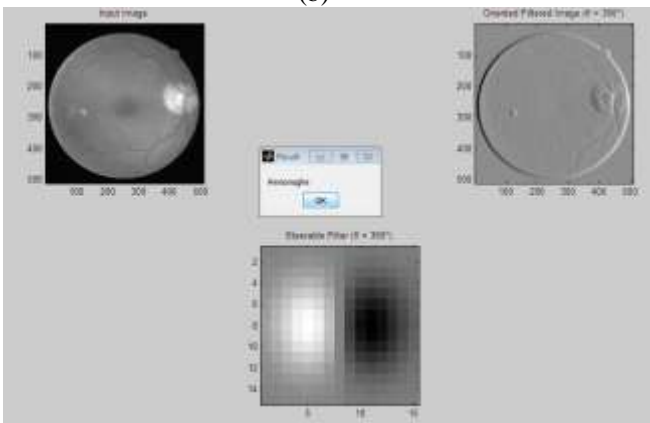
The ultimate goal of retinal hemorrhage detection using feature classification is to detect whether the image consisting of hemorrhage or not. After extracting features, selecting a set of relevant extracted features are finally used for feature classification. The following results shows detection of small, large hemorrhages and normal images.



(a)



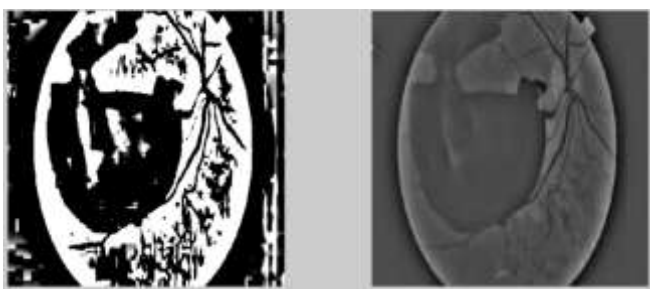
(b)



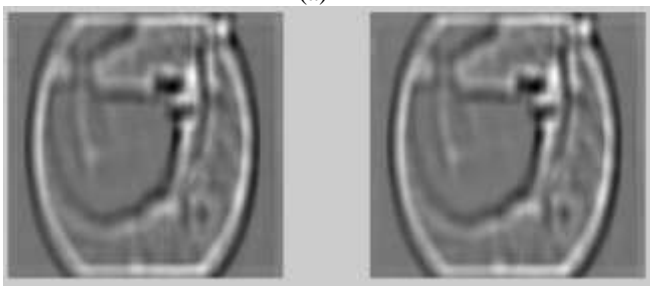
(c)

Fig.5 (a) DoG filter result having $\sigma = 16$ and $\sigma_0 = 0.5$ (b) First and second order derivatives of Gaussian filter bank. (c) Steerable filter result.

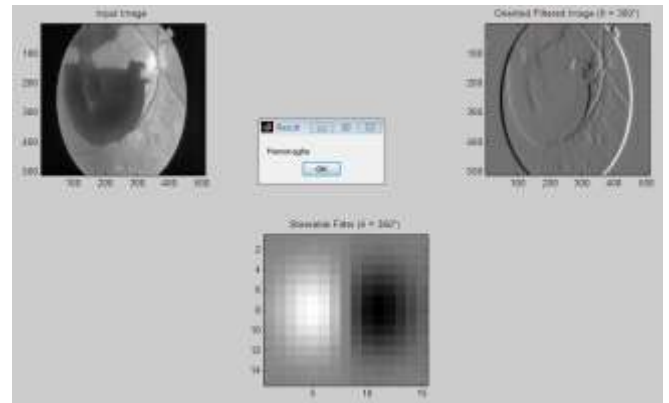
Figure 6 shows detection of large hemorrhage.



(a)



(b)



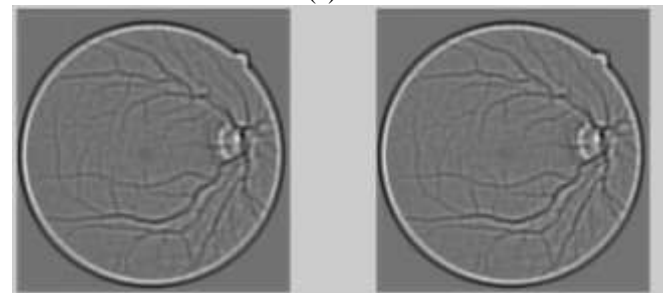
(c)

Fig 6. (a) DoG filter result of large hemorrhage having $\sigma = 16$ and $\sigma_0 = 0.5$. (b) first and second order derivatives of Gaussian filter bank. (c) Steerable filter result.

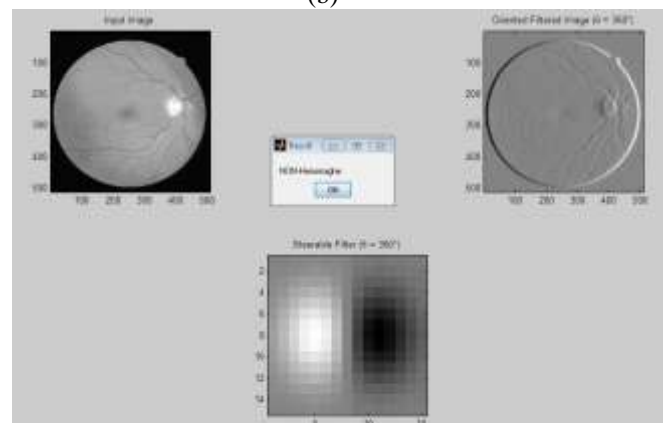
The following figures shows detecting retinal images without having any hemorrhages. i.e., detection of normal images.



(a)



(b)



(c)

Fig7. (a) DoG filter result having $\sigma = 16$ and $\sigma_0 = 0.5$ (b) First and second order derivatives of Gaussian filter bank. (c) Steerable filter result.

4. Conclusion

Diabetic retinopathy is one of the vascular complications in retina, which is related to diabetes. Diabetic eye problem is because of damage of small vessels in eye. It can result in severe loss of vision or even blindness. Feature classification method is useful for the early detection of retinal hemorrhages.

Major advantage of using this technique is that, it is fast and easy to detect the abnormalities. Image level interpretation is also possible through performing the difference of first and second order derivatives from green channel result. A set of features are extracted and relevant features used for the final feature classification. So, this technique is useful for detecting small and large retinal hemorrhages also for checking normal retinal images.

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