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Splat Feature Classification With Application to Retinal Hemorrhage Detection in Fundus Images

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Abstract:
In this paper, a splat feature classification method for retinal hemorrhage detection is presented. The detection of retinal hemorrhages is most important in the automated screening system to find out the diabetic retinopathy diseases. Here the retinal images are divided into non-overlapping segments. For each segment, contains pixels with same color and spatial location. A set of features is extracted to describe its characteristics such as splat area, splat extent, splat orientation, texture features etc. These features are selected by using the filter approach followed by Wrapper approach. After the feature selection step, the classifier is used to calibrate the feature space and its discriminative characteristics. The Accuracy of splat labels are finding out by the classification techniques and detect the retinal hemorrhages in a fundus images.

Key words*: Diabetic retinopathy, retinal hemorrhages, splat features, Fundus image*

1. Introduction

Eye is like a camera. The eye is a slightly asymmetrical globe, about an inch in diameter. The external object is seen like the camera which takes the picture of an object. Light enters the eye through a small hole called the pupil and is focused on the retina. Eye also has a focusing lens, which focuses image from different distances on the retina. The eye generally consists of three layers such as, Fibrous layer, Vascular layer, and Nerve layer. In this the nerve layer contains retina which is a multi-layered sensory tissue. It contains millions of photo receptors to capture the light rays and convert them into electrical impulse and it pass through the optic nerve to brain. If any damage occurs in this, it causes retinal disorders. Such as, Diabetic retinopathy, Vitreous hemorrhages etc.

Diabetic retinopathy is the leading cause of blindness in the working population of the western world. It is a most common disease which occurs when blood vessels in the retina change. Sometimesthese vessels swell and leak fluid and then causeretinal hemorrhages. The retinal hemorrhages are a tiny spots of blood that leak into retina. New blood vessels bleed into the Vitreous is termed as Vitreous hemorrhages. The vitreous is the gel in the center of the eye preventing light rays from reaching the retina. Since very large hemorrhages might block out all the vision. Then the Automated detection of diabetic retinopathy is used in screening systems for allowing timely treatment.

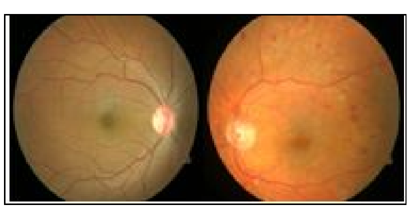

Figure 1: Images for Normal eye and Retinal hemorrhage affected eye

It is used to prevent visual loss and blindness. The most common signs of DR are micro aneurysms, small hemorrhages, exudates, drusen, and cotton wool spots etc.The retinal hemorrhage is a disorder of the eye in which bleeding occurs into the retentive tissue on the back wall of the eye. It can be caused by hypertension, retinal vein occlusion or diabetic mellitus. The Retinal Hemorrhages that take place outside of the macula can go undetected for many years, it can be picked up by using the ophthalmoscopy, fundus photography or a dilated fundus exam techniques. The retinal images are classified into small hemorrhages and large hemorrhages. The small hemorrhages are regular in shape and the large hemorrhages are occurring infrequently.

Diabetic retinopathy is a common eye problem associated with diabetes by stressing the circulatory system. It can cause damage, including hemorrhaging to the small blood vessels of the retina. When the damaged or leaking blood vessels do not spread in nonproliferative retinopathy. Proliferative retinopathy occurs when new blood vessels begin to form in damaged areas of the retina and may lead to spot, decreased vision, or sudden loss of vision. And the recent work is going on about the retinal hemorrhages. By using three approaches to find out the retinal disorders such as, Pixel based approaches, lesion based approaches and image based approaches. The pixel based approaches are used to find out the location of hemorrhages on the retina. The lesion based approaches are used to find out the morphological operations and the image based approaches are used to detecting the eyes with hemorrhages. Detecting the DR lesions or hemorrhages is often skilled by using the supervised classification and the features are extracted from each pixel. Finally the features are classified to detect the level of the retinal hemorrhages.

2. Materials and Methods

The methods and materials used in this proposed paper is,

2.1. Fundus Fluorescein Angiography

It is a technique that observing the vessels of the fundus of the eye and iris by using photography. It is also used to see the details of retina or back part of the eye which is not visible with naked eyes. This procedure requires high quality of camera with excellent computerized digital system and fluorescein dye. Fluorescence is a property of substance to alter the wavelength of the reflected light on exciting. Angiography means recording of the angious or the blood vessels. It is basically recording and visualization of the blood vessels of the retina using fluorescein dye. It provides three information's such as,

- The flow characteristics in the blood vessels, as the dye reach and circulate through the retina and choroid.
- It records fine details of the pigment epithelium and retinal circulation that may not be visible.
- Give a clear picture of the retinal vessels and assessment of their functional integrity.

2.2. Image processing Techniques

Digital image processing refers to processing of the image in digital form. Modern cameras may directly take the image in digital form but generally images are originated in optical form they are captured by video cameras and digitalized. Then these images are processed by five fundamental processes such as, image enhancement, image restoration, image analysis, image compression and image synthesis. For medical applications the images may be used for patient screening and monitoring or for detection of tumours or other disease in patients.

3. Methods

The novel splat feature classification method is presented with the application to retinal hemorrhages detection in fundus images.The figure 2 shows the block diagram of work plan.

3.1. Splat Segmentation

Image segmentation is the process of dividing an image into multiple parts. This is typically used to identify objects or other relevant information in digital images. The images are partitioned into non-overlapping segments such as the pixel contains same color and spatial locations. Splat based representation is an image resampling technique for an irregular grid. This technique is used to maximize the diversity of training samples. To separate the boundaries of hemorrhages from retinal background using scale specific image over segmentation. It performs in two steps,

- Separating the blood and retinal background by using gradient magnitude technique.
- To perform watershed segmentation.

In the pre-processing stage the filters are used to reduce the noise and improve the quality of an image. For the splat features the directional change in the intensity or colour of an image the gradient magnitude technique is used. It establishes a scale space representation of an image with Gaussian kernalsG_s at scale-of-interest (SOI). The high frequency noises are reduced by this technique.

The splats are created by over-segmenting images using watershed algorithms. The watershed transform can be classified as a region based segmentation approach. As a result, the landscape is partitioned into regions or basins separated by dams, called watershed lines or watersheds. A splat-based approach divides the images into an irregular grid, depending on the properties of target objects to be detected. The watershed transform is defined as, Let Let $f \in C(D)$ have minima $\{m_k\}_{k \in i}$ for some index set I. the catchment basin $CB(m_i)$of a minimum $m_i$is defined as the set of points $x \in D$ which are topographically closer to $m_i$than to any other regional minimum m_j

$$CB(m_i) = \{x \in D \mid \forall j \in I\{i\} : f(m_i) + T_f(x, m_i) < f(m_j) + T_f(x, m_j)\}$$

The watershed of $f$is the set of points which do not belong to any catchment basin:

$$Wshed(f) = D \cap \left(\bigcup_{i \in I} CB(m_i) \right)^c$$

Where,
Wshed represents the watershed and Let $W \in I$. So the watershed transform assigns labels to the points of *D*.
CB is the catchment basin, *f* is an image element.

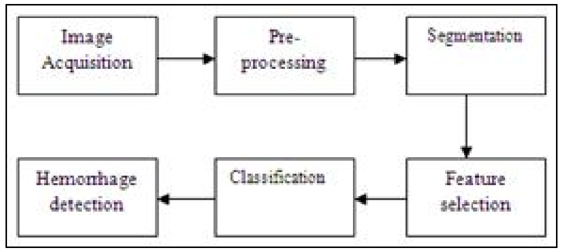

Figure 2: Work plan block diagram

By this segmentation process the edge effects are removed and vignetting in fundus photographs. And the features are extracted according to the grey level co-occurrence matrix (GLCM). Spalt features are extracted from each spalt to describe its characteristics relative to its surroundings, shape and texture information. The splat features are extracted by using Gaussian filter bank to remove the unwanted noises in an image.

3.2. Feature selection

The feature selection is a process used to evaluatethe discrimination power of candidate features. It is used to reduces the dimensionally of feature space by identifying the relevant features and ignoring the irrelevant features. The sequential feature selection is a most popular feature selection Algorithms. It shows how to use hold out and cross validation to evaluate the performance of the selected features. Reducing the number of features is important in statistical learning. For many datasets with a large number of features and a limited number of observations such as splat feature data. But many features are not useful for producing a desired learning result it also over fit to the noise. Reducing features can also save storage and computation time also increases compatibility. In this paper two approaches are used to select the features.

- Filter approach
- Wrapper approach

In this filter approach leads the classification process. It is independent of the learning induction algorithm.This approach is simple fast and scalable. The filter approach is used for the high dimensional feature space, when compare to wrapper approach the filter approach is fast. The wrapper approach is a program that extracts content of a particular information source and translates it into a relational form. It is a feature selection algorithm is interleaved with the classifier as opposed to the filter approach, in which a feature subset is selected once before serving the classifier. In this the features are classified into strongly relevant, weak relevant, and all the others are feature irrelevant.

3.3. Filter approach followed by wrapper approach

Here the two step feature selection process is used to compare the advantages of both approaches. The datas are classified into training set and testing set. The filter approach is used for preliminary feature selection with a filter approach. The preliminary selection is used to separate the relevant and irrelevant hemorrhages. And for each features the t-test is applied and find out the p-values, which measures the effectiveness of splats. The selected features are plotted in the increasing order and the remaining irrelevant features are getting removed. After the preliminary selection the irrelevant features are removed. By using the wrapper approach the redundancy of the relevant features are minimized. To evaluate the potential abilities the classification algorithm is used. The accuracy of the splat labels are found out by the K-NN Classifier algorithm.

3.4. KNN Classifier Algorithm

In pattern recognition the K-NN is a non-parametric method used for classification and regression. The input consists of the k-closest training examples in the feature space. The output depends on whether K-NN is used for classification or regression. Training examples are vectors in a multidimensional feature space each with a class labels. The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples. The KNN classifier is used to reduce the computational load. There are two difficulties with the practical exploitation of the power of the K-NN approach. First, while there is no time required to estimate parameters from the training data, the time to find the nearest neighbours in a large training set can be prohibitive. To overcome the difficulties,

- Reduce the time taken to compute distances by working in a reduced dimension using dimension reduction techniques such as principal components.
- Use sophisticated data structures such as search trees to speed up identification of the nearest neighbor. This approach often settles for an almost neighbor to improve speed.
- Edit the training data to remove redundant or almost redundant points in the training set to speed up the search for the nearest neighbor.
- To remove the samples in the training data set that has no effect on the classification because they are surrounded by samples that all belong to the same class.

In this project each sample in the data set has n attributes which combine to form an n-dimensional vector.

$X = X_1, X_2, \dots\dots, X_n$

Where, *n* attributes are considered to be variables. Another attributes are denoted by *y*. The value depends on other *n* attributes *X*. The value y defined as,

$y = f(X)$

f is a scalar function and *y* is a categorical variable the probability of splat from hemorrhages itself. The probability value *p*was determined by,

$p = n/k$

The distance of the nearest neighbor can be measured by using Euclidean metric in the optimized feature space,

$$d(x,u) = \sqrt{\sum_{i=1}^{n} (x_i - u_i)^2}$$

Where, d(x,u) is to measure the distance between the points in the space of independent predictor variables. Finally it classifies the splat features such as splat size, splat orientation, splat area, splat solidity and texture features. The main goal of the splat feature classification is to develop a hemorrhage detector for indicating whether the image was in normal condition or abnormal conditions.

To eliminate the hemorrhageness map *h*, the low probability values are suppressed by using,

$$h(x,y) = \begin{cases} h(x,y) & if\ h(x,y) \geq h_0 \\ 0 & if\ h(x,y) < h_0 \end{cases}$$

Where h_0 is a pre-defined threshold.

The appropriate value can be chosen according to the training set by collecting the probabilities of both hemorrhages and non-hemorrhages splat and then the relevant objects are detected. Here the two groups of splat probabilities are sorted by using the ROC curve which ranges from 0 to 1 in Figure 3. The non-hemorrhage splats are classified with very low probabilities, the threshold value h_0 = 0.2 in this the false positives would be suppressed.

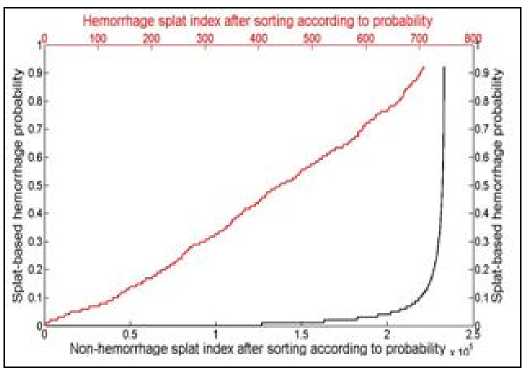

Figure 3: Probabilities assigned to hemorrhage splats and non-hemorrhage splatsin the training set

In figure 4, the splat level accuracy was achieved on 0.96 on the testing set and the system can operate at a sensitivity of 93% and specificity of 66% on an image basis.

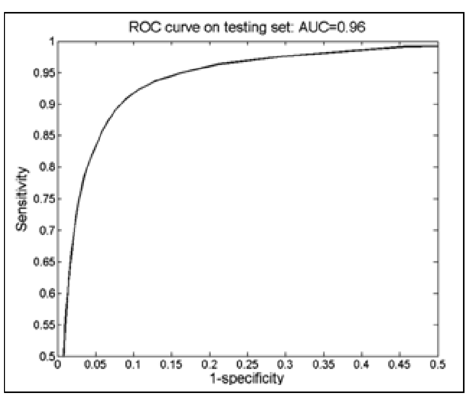

Figure 4: Splat-based ROC curve with an AUC of 0.96 on the testing set.

4. Results

In this paper, the splat feature classification algorithm is used for the application to find out the large and irregularhemorrhages in the fundus photographs. It is important in the development of automated screening systems. In this proposed method, to partitioning the retinal images and the extracted features are classified by using the watershed transform and the K-NN classifier algorithms.By using the watershed transform which is used to separate the boundaries of hemorrhages from retinal images. And it can be used to classify its splat features in Figure 5.

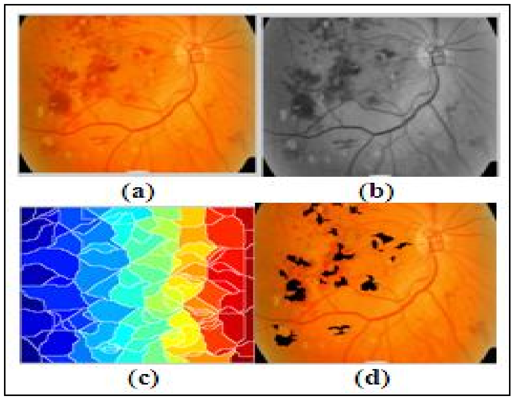

Figure 5: Watershed Transform outputs

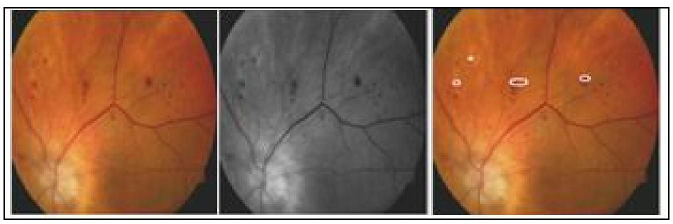

Figure 6: K-NN classifier outputs

By the segmentation process the edge effects are removed in the fundus photographs. The grey level of a pixel is interpreted as its altitude in the relief. The watershed transformation considers the gratitude magnitude of an image as a topographic surface in Figure 5(c). Finally it applied to the marked gradient images to get the output. Finally the KNN classifier is used to detect the hemorrhages in Figure 6(c).

5. Discussions and Conclusion

Splat feature classification with application to retinal hemorrhage detection in fundus images is the key step in diabetic retinopathy screening systems. The retinal blood vessels are act as the landmarks for other structures such as optic disc and fovea. This requires the reliable process of splat feature classification methods. In the past years, several approaches for extracting the retinal images and classify its features have been developed which can be divided into two groups; one consists of supervised classifier based algorithms and other one is induction based algorithms. A supervised classifier algorithm produces segmentation of spatially connected regions. These regions are then classified as hemorrhage or non-hemorrhage. In this study the regions are segmented by a user defined threshold which is classified as whether the hemorrhages occur or not according to their length-to-width ratio.

In the study by Leandro et al[3] the application of mathematical morphology and wavelet transform was investigated for identification of retinal blood vessels. In a follow up study, to compute the gradient magnitudes of the input image at scales optimal for localization of vessel boundaries. In these gradients over scales is performing by watershed segmentation. For splat segmentation, a Gaussian kernel approaches are used to separate the blood and non-blood regions by using the splat feature space algorithm.

In the study of 42 features were selected and to be extracted from the testing dataset for splat based feature classification by L. Tang et al[13]. One drawback to these approaches is only extracted features shared by the vasculature and hemorrhages, and the more extensive testing is required in this approach. In a paper by Michael D. Abramoff et al[10], the automated early detection of diabetic retinopathy using the eye check algorithm and to detect the disease. The drawback in this paper is that they detect the red lesions only but not exudates, cotton-wool spots.

In the current study, a novel splat feature classification method by using K-NN classifier and watershed transform technique. The results suggest that the features are extracted for splat based responses. For splat segmentation, watershed transform is used. To reduce the over segmentation of images K-NN classifier is used. The Neural Network based on supervised algorithms requires labeled samples by experts, but it is expensive to acquire the data. To avoid this limited number of training sample is selected by using the splat-based image formulation technique. This will increase the system performance. The overall sensitivity of a system performance is 93% and specificity is 66% and the threshold value is set to 0.2 Fps on per image basis.

In order to compare the results with the most relevant works, the performance of different algorithms had evaluated by using Messidor dataset and DRIVE dataset. The area under the ROC curve in this method reached a value of 0.96 in the present application the threshold value h_0=0.2 and the false positives would be suppressed. The previously reported accuracies are ranges from 0.787 to 0.961.

In conclusion, the proposed splat feature classification technique does not require any user intervention. It is able to model shapes of various lesions effectively. The approach is achieved an area under splat wise ROC curve is 0.96 which is higher than the previous methods. The hemorrhage and non-hemorrhages are selected by using the KNN classifier and watershed transformation successfully. Hence the hemorrhages are detected and the screening systems assisting opthalmologists in the detection of diabetic retinopathy.

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