Splat Feature Classification with Retinal Hemorrhage Detection in Diabetic Patients

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Abstract

A novel splat feature classification method is presented with application to retinal hemorrhage detection in fundus images. Reliable detection of retinal hemorrhages is important in the development of automated screening systems which can be translated into practice. Automated detection of diabetic retinopathy (DR), as used in screening systems, is important for allowing timely treatment and thereby increasing accessibility to and productivity of eye care providers. Because of its cost-effectiveness and patient friendliness, digital color fundus photography is a prerequisite for automated DR detection. Patients with images that are likely to contain DR are detected and referred for further management by eye care provides. Under this supervised approach, retinal color images are partitioned into non overlapping segments covering the entire image. Each segment contains splat, pixels with similar color and spatial location. A set of features is extracted from each splat to describe its characteristics relative to its surroundings and responses from a variety of filter bank, interactions with neighboring splats, shape and texture information. An optimal subset of splat features is selected by a filter approach followed by a wrapper approach. The general characteristics of training data are used to select features. The wrapper method searches for an optimal feature subset tailored to a particular algorithm and a domain. Improvement in accuracy is achieved for some datasets for the two families of induction algorithms used: decision trees and Naive-Bayes. In addition, the feature subsets selected by the wrapper are significantly smaller than the original subsets used by the learning algorithms, thus producing more comprehensible results.

Keywords: Diabetic Retinopathy(DR), Fundus image, Retinal Hemorrhage, Splat Feature Classification, SVM& KNN.

1. Introduction

Diabetic retinopathy(DR) is a major public health issue since it can lead to blindness in patients with diabetes. Early treatment can prevent patients to become affected from this condition or at least the progression of DR can be slowed down. The most

Hyperglycemia damages the retinal vessel walls, which can lead to:

1.1. Ischemia, resulting in the growth of new blood vessels, which may subsequently bleed and/or cause retinal detachment, condition called proliferative diabetic retinopathy;

1.2. Breakdown of the blood-retinal barrier, leading to fluid leakage, diabetic macular edema (DME) and damage to photoreceptors.

Common signs are micro aneurysms, small hemorrhages, exudates, druses and cotton wool spots. Because of the variability in appearance of these lesions, different techniques have been designed to detect each type separately. In the eye

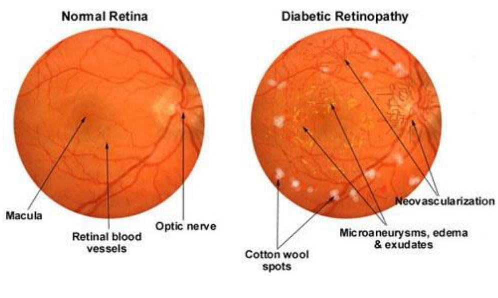

Fig: 1: Normal and affected Retina

2. Types of Diabetic Retinopathy

Diabetic retinopathy is classified into two types.

- Non-proliferative diabetic retinopathy (NPDR) is the early stage of the disease in which symptoms will be mild or nonexistent.
- Proliferative diabetic retinopathy (PDR) is the more advanced form of the disease.

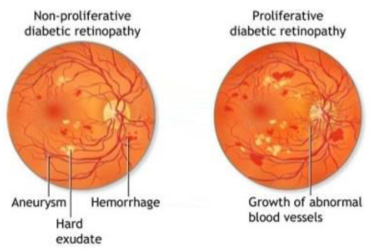

Fig:2: Types of Diabetic Retinopathy

3. Steps involved in retinal hemorrhage detection

The steps involved in retinal hemorrhage detection using splat feature classification technique are as follows:

3.1.Data read
3.2. Enhancement
3.3. GradientMagnitude & Splat segmentation process
3.4. Watershed segmentation
3.5. Hemorrhage mapping

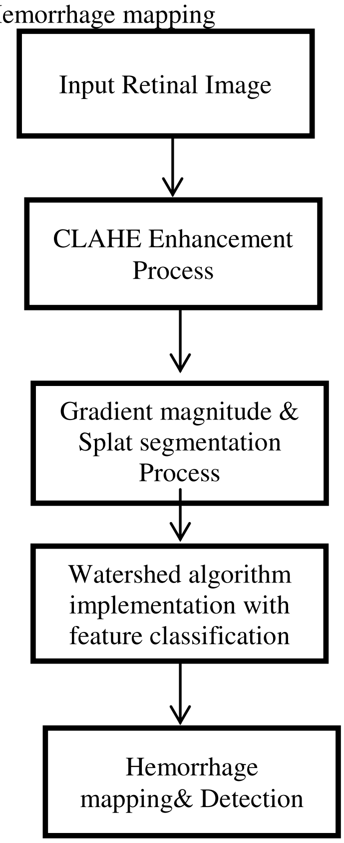

Fig: 3: Architecture for hemorrhage detection

3.1. Data Read

Get a retinal image as an input from the data set for the hemorrhage detection.

3.2. Enhancement Adaptive histogram equalization

(AHE) is a computer image processing technique used to improve contrast in images. It differs from ordinaryhistogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast of an image. However, AHE has a tendency to over amplify noise in relatively homogeneous regions of an image. A variant of adaptive histogram equalization called Contrast Limited Adaptive Histogram Equalization (CLAHE) prevents this by limiting the amplification.

3.3.Gradient Magnitude & Splat segmentation process

- An image gradient is a directional change in the intensity or color in an image. Image gradients may be used to extract information from images.We firstly aggregate gradient magnitudes of the contrast enhanced dark-bright opponency image at a range of scales for localization of contrast boundaries separating blood and retinal background.
- The splat segmentation is used for extract the region from retinal data which is shows the hemorrhage region identification in fundus image
- The term gradient or color gradient is used for a gradual blend of color which can be considered as an even gradation from low to high values, as used from white to black in the images to the right. Another name for this is color progression. It is important to obtain meaningful splats preserving hemorrhage boundaries precisely

3.4. Watershed algorithm implementation with feature classification

UsingWatershed algorithm we can detect the hemorrhage region in retinal areas with respective to shed based approaches in image sizing.

3.5.Retinal Hemorrhage Mapping

Retinal hemorrhage is a disorder of the eye in which bleeding occurs into the light sensitive tissue on the back wall of the eye .A retinal hemorrhage can be caused by hypertension, retinal vein occlusion (a blockage of a retinal vein),or diabetes mellitus (which causes small fragile blood vessels to form,which are easily damaged).Retinal hemorrhages can also occur due to shaking,particularly in young infants (shaken baby syndrome)or from sever blows to the head.

Retinal hemorrhages that place outside the macula can go undetected for many years and may sometimes only be picked up when the eye is examined in detail by ophthalmoscopy, fundus photography, or a dilated fundus exam. However, some retinal hemorrhages can cause severe impairment of vision. They may occur in connection with posterior vitreous detachment or retinal detachment.

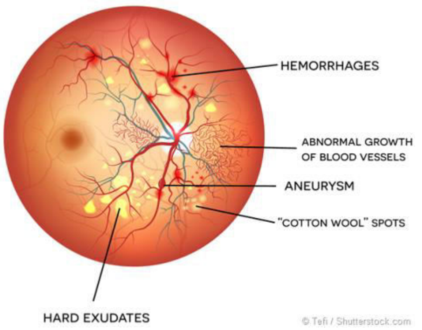

Fig: 4: Diabetic Retinopathy Hemorrhages

4. Algorithmsinvolved in retinal hemorrhage detection

4.1.SVM

"Support Vector Machine" (SVM) is a supervised machine learning algorithm which can be used for both classification and regression challenges. However, it is mostly used in classification problems. In this algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiate the two classes very well (look at the below snapshot).

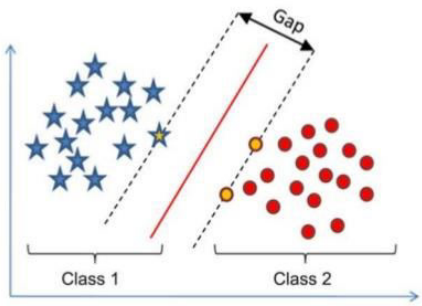

Fig:5: Basic Concept of SVM

Support Vectors are simply the co-ordinates of individual observation. Support Vector Machine is a frontier which best segregates the two classes (hyper plane/ line).

4.2. KNN

The most popular classifier is KNN (K nearest neighbor) algorithm. KNN is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure. This technique compares data with nearest data to make classification. Distance between the data point is crucial in this technique. Data points between training and testing data are iteratively modified to give the appropriate result.

4.2.1. KNN Works

- Determine K (No of nearest neighbors)
- Calculate distance (Eucildean,Manhattan)
- Determine K-minimum distance Neighbors
- Gather Category y values of nearest neighbors
- Use simple majority of nearest neighbor to predict value of query instance.

4.3. Watershed Algorithm

A **watershed** of a gray scale image is analogous to the notion of a catchment basin of a height map. In short, a drop of water following the gradient of an image flows along a path to finally reach a local minimum. Intuitively, the watershed of a relief corresponds to the limits of the adjacent catchment basins of the drops of water.There are different technical definitions of a watershed. In graphs, watershed lines may be defined on the nodes, on the edges, or hybrid lines on both nodes and edges. Watersheds may also be defined in the continuous domain. There are also many different algorithms to compute watersheds. Watershed algorithm is used in image processing primarily for segmentation purposes.

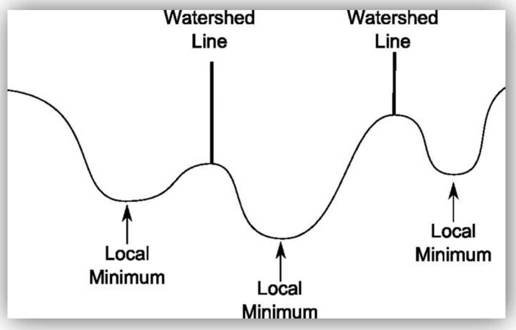

Fig 6: Principle of watershed algorithm

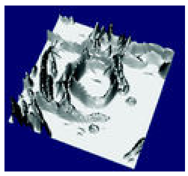

Fig: 7: Relief of the gradient Magnitude

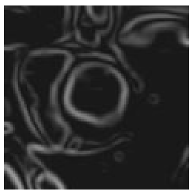

Fig: 8: Gradient magnitude image

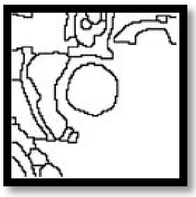

Fig: 9: Watershed of the gradient

A watershed is a basin-like landform defined by highpoints and ridgelines that descend into lower elevations and stream valleys.

Watershed algorithm steps are as follows

- Step 1: Read in the Color Image and Convert it to Gray scale.
- Step 2: Use the Gradient Magnitude as the Segmentation Function.
- Step 3: Mark the Foreground Objects.
- Step 4: Compute Background Markers.
- Step 5: Compute the Watershed Transform of the Segmentation Function.
- Step 6: Visualize the Result.

5. Conclusion

Splat feature classification technique can be used to detect large irregular retinal hemorrhages with less probability for false positive. Large hemorrhages are irregular in shape with wide range of characteristics. Many of the hemorrhage splat overlaps with the blood vessels and results in misclassification. Splat based image representation makes it easier for clinicians to annotate the boundaries of target objects which may lower the cost of acquiring reference standard data for training.

Aggregating features within splats improves their robustness and stability, as it is resistant to pixel level noise and intensity bias. Splat-based feature classification is able to model shapes of various lesions efficiently regardless of their variability in appearance, texture or size. A variety of lesion detection tasks can therefore be generalized into exactly the same framework by training classifiers with optimal features learned from available examples projected onto a sub-feature space which maximizes the inter-class distances while minimizes the intra-class distance.

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