Retinal Hemorrhage Detection in Fundus Image using Splat Approaches

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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. Under our supervised approach, retinal color images are partitioned into non overlapping segments covering the entire image. Each segment, i.e., splat, contains pixels with similar color and spatial location. A set of features is extracted from each splat to describe its characteristics relative to its surroundings, employing responses from a variety of filter bank, interactions with neighbouring splats, and shape and texture information. An optimal subset of splat features is selected by a filter approach followed by a wrapper approach. In Future, we measure the performance analysis of blood vessels extractions with classifier for improving the accuracy.

Keywords: Diabetic retinopathy (DR), fundus image, retinal hemorrhage, splat feature classification.

I. INTRODUCTION

Diabetic retinopathy often has no early warning signs. Even macular edema, which may cause vision loss more rapidly, may not have any warning signs for some time. In general, however, a person with macular edema is likely to have blurred vision, making it hard to do things like read or drive. In some cases, the vision will get better or worse during the day. On the first stage which is called Non-proliferative diabetic retinopathy (NPDR) there are no symptoms, are not visible to the naked eye and have 20/20 vision, but can be detected by fundus photography. In the photo we can see micro aneurysms (microscopic blood-filled bulges in the artery walls). If there is reduced vision, fluoresce in angiography can be done to see the back of the eye. Narrowing or blocked retinal blood vessels can be seen clearly and it is called retinal ischemia (lack of blood flow). Macular Oedema may occur in which blood vessels leak contents into the macular region can happen at all stages of NPDR. The macular Oedema symptoms are blurring, darkening or distorted images with not the same between two eyes. 10 percent of diabetic patients will get vision loss related with macular Oedema. Optical Coherence Tomography can show areas of retinal thickening (fluid accumulation) of macular Oedema.

On the second stage, as abnormal new blood vessels (neo vascularisation) form at the back of the eye as a part of proliferative diabetic retinopathy (PDR), they can burst and bleed (vitreous hemorrhage) and blur vision, because the new blood vessels are weak. The first time this happens, it may not be very severe. In most cases, it will leave just a few specks of blood, or spots, floating in a person's visual field, though the spots often go away after a few hours. These spots are often followed within a few days or weeks by a much greater leakage of blood, which blurs vision. In extreme cases, a person will only be able to tell light from dark in that eye. It may take the blood anywhere from a few days to months or even years to clear from the inside of the eye, and in some cases the blood will not clear. These types of large hemorrhages tend to happen more than once, often during sleep.

A. *Retinopathy*

Retinopathy is the name given to 'disease of the retina' due to diabetes.

1) *Types Of Retinopathy*

There are four main types of retinal damage that can occur if you are diabetic. Unfortunately the condition may progress from no or mild retinopathy to a much more severe type.

- No retinopathy…. many people have a basically healthy retina. If you can control your diabetes and blood pressure at this stage it will help prevent or slow down any harmful changes.
- Background retinopathy…. early changes.
- Maculopathy ….this is more serious. Eventually your sight may become reduced. Laser and blood pressure control help.
- Pre-proliferative or non-proliferative stages before the new blood vessels start growing.
- Proliferative retinopathy … when the new vessels grow. These blood vessels are very delicate and can bleed easily. Laser is very effective in stopping the new vessels grow.

II. HEMORRHAGE DETECTION

Bleeding, technically known as hemorrhaging or hemorrhaging, is the loss of blood or blood escaping from the circulatory system. Bleeding can occur internally, where blood leaks from blood vessels inside the body, or externally, either through a natural opening such as the mouth, nose, ear, urethra, vagina or anus, or through a break in the skin. Desanguination is a massive blood loss, and the complete loss of blood is referred to as exsanguinations. Typically, a healthy person can endure a loss of 10–15% of the total blood volume without serious medical difficulties, and blood donation typically takes 8–10% of the donor's blood volume. 1

A. *SPLAT SEGMENTATION*

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*

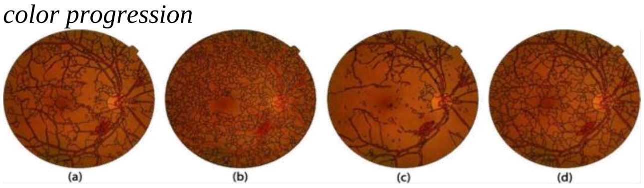

Fig. 1: Scale-specific image over-segmentation create splats preserving hemorrhage boundaries.

Watershed algorithm with topographic surface obtained as (a) maximum of gradient magnitude from desired scale band; (b) pixel intensity; (c) gradient magnitude from a fine scale outside scale-of-interest; (d) gradient magnitude from a coarse scale outside scale-of-interest.

In Fig1 Each image in this figure contains a similar number of splats generated by the same watershed algorithm. It reveals that splat distribution depends closely upon the method of acquiring a gradient image. In Fig. 1(a), high-frequency noise at finer scales such as those in Fig. 1(c) is removed and splats boundaries are

accurately aligned with boundaries of blood regions instead of being trapped at other contrast magnitudes as those shown in Fig. 1(d). Details related with blood regions are represented by small splats and retinal background consists of much larger splats in Fig. 1(a). Given similar number of splats, those in Fig. 1(d) have more uniform sizes. The scale in Fig. 1(d) may be more appropriate in dealing with structures such as optic disc while that in Fig. 1(c) may be more appropriate in dealing with micro aneurysms, drusen, etc.

B. SPLAT FEATURE EXTRACTION

Extract the splat features in retinal fundus image in numerical wise GLCM (Gray level co occurrence matrix) features are extracted from hemorrhage fundus image from the subset of data after mapping with fundus image. Graycomatrix calculates the GLCM from a scaled version of the image. By default, if I is a binary image, graycomatrix scales the image to two gray-levels. If I is an intensity image, graycomatrix scales the image to eight gray-levels. It specifies the number of gray-levels graycomatrix uses to scale the image by using the 'NumLevels' parameter, and the way that graycomatrix scales the values using the 'Gray Limits' parameter.

1) Filters Bank

Using Various filters, Local texture filters include local range filter, local standard deviation filter and local entropy filter, which compute the intensity range (contrast), standard deviation and entropy of one pixel in a given neighborhood or region with homogeneity .

$$G(X) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-x^2}{2\sigma^2}}$$

There are 3 main types of texture filtering:

Nearest - Nearest filtering will just take the pixel color of the single pixel that is closest to the texture coordinates it is currently trying to sample at. Nearest filtering will make the image look more pixelated, but can be useful when trying to get pixel perfection.

Linear - Linear filtering, also known as interpolation, will blend of the 4 pixels closest to the coordinate where the GPU is currently sampling.

Mipmap Linear - Mipmap linear, also known as Trilinear, is Linear Filtering, with the addition of sampling and blending between two different mipmap levels.

2) KNN CLASSIFICATION

The k-nearest neighbor’s algorithm (k-NN) is a non-parametric method for classification and regression that predicts objects, values or class memberships based on the k closest training examples in the feature space. K-NN is a type of instance-based learning, or lazy learning where the function is only approximated locally and all computation is deferred until classification. The k-nearest neighbor algorithm is among the simplest of all machine learning algorithms: an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor. kNN classification classifies instances based on their similarity to instances in the training data. The conditionals of the form P(Xi/Y) are estimated by counted to number of co-occurrences of the pairs (Xi,Y) in the training data. It Uses local information and is susceptible to noise in the training data . KNN assumes that the data is in a feature space. More exactly, the data points are in a metric space. The data can be scalars or possibly even multidimensional vectors. Since the points are in feature space, they have a notion of distance (Euclidean distance).

C. CLASSES OF HEMORRHAGE

– *Class I Hemorrhage* involves up to 15% of blood volume. There is typically no change in vital signs and fluid resuscitation is not usually necessary.
– *Class II Hemorrhage* involves 15-30% of total blood volume. A patient is often tachycardic (rapid heart beat) with a narrowing of the difference between the systolic and diastolic blood pressures. The body attempts to compensate with peripheral vasoconstriction. Skin may start to look pale and be cool to the touch. The patient may exhibit slight changes in behavior. Volume resuscitation with crystalloids (Saline solution or Lactated Ringer's solution) is all that is typically required. Blood transfusion is not typically required.
– *Class III Hemorrhage* involves loss of 30-40% of circulating blood volume. The patient's blood pressure drops, the heart rate increases, peripheral hypoperfusion (shock), such as capillary refill worsens, and the mental status worsens. Fluid resuscitation with crystalloid and blood transfusion are usually necessary.
– *Class IV Hemorrhage* involves loss of >40% of circulating blood volume. The limit of the body's compensation is reached and aggressive resuscitation is required to prevent death.

III. RELATED WORKS

As reviewed in[1] M. D. Abramoff, J. M. Reinhardt, S. R. Russell, J. C. Folk, V. B. Mahajan,M. Niemeijer, and G. Quellec, Diabetic retinopathy (DR) is the most common cause of blindness in the working population of the United States and of the European Union.1Early detection and timely treatment have been shown to prevent visual loss and blindness in patients with retinal complications of diabetes. In the next decade, projections for the United States are that average age will increase, the number of people with diabetes in each age category will increase, and there will be an undersupply of qualified eye care providers, at least in the near term. This so-called perfect storm of healthcare trends will challenge the public health capacity to care for both patients with DR and people with diabetes at risk for this complication.6If the previous scenario plays out, it will be necessary either to screen (perform early detection on) large numbers of people with diabetes for DR, to ration access to eye care, or both Evaluation of diagnostic test or technology. Participants: Fundus photographic sets, consisting of 2 fundus images from each eye, were evaluated from 16 670 patient visits of 16 670 people with diabetes who had not previously been diagnosed with DR. The fundus photographic set from each visit was analyzed by a single retinal expert; 793 of the 16 670 sets were classified as containing more than minimal DR (threshold for referral). The outcomes of the 2 algorithmic detectors were applied separately to the dataset and were compared by standard statistical measures.

As reviewed in[5] G. Quellec, S. Russell, and M. Abramoff, Automated detection of lesions in retinal images is a crucial step towards efficient early detection, or screening, of large at-risk populations. In particular, the detection of micro aneurysms, usually the first sign of diabetic retinopathy (DR), and the detection of drusen, the hallmark of age-related macular degeneration (AMD), are of primary importance. In spite of substantial progress made, detection algorithms still produce 1) false positives—target lesions are mixed up with other normal or abnormal structures in the eye, and 2) false negatives—the large variability in the appearance of the lesions causes a subset of these target lesions to be missed. The reference image samples are obtained either from an expert- or a data-driven approach. Factor analysis is used to derive the filters generating this feature space from reference samples. Previously unseen image samples are then classified in this feature space. We tested this approach by training it to detect micro aneurysms. On a set of images from 2739 patients including 67 with referable DR, DR detection area under the receiver-operating characteristic curve (AUC) was comparable to our previously published red lesion detection algorithm. Recent studies have shown that quantitative measures of the retinal microvasculature predict cardiovascular disease. Digital fundus imaging in ophthalmology plays an important role in medical diagnosis of primary levels of diabetes and blood pressure as well as cardiovascular disease. Thick vessels also display a higher contrast with the background than do thin ones. Moreover, presence of noise, fovea and optical disk as well as vessels with various widths, effects of lesions, and pathological changes are the other cases to be considered. Therefore, presence of an automatic blood vessel detection tool that segments the blood vessels of retina in a short time and with high accuracy is our desire. The cross section of a vessel in a retinal image was modeled by a Gaussian-shaped curve in and then detected using rotated matched filters. Classifier-based methods perform in two stages. First, a low-level algorithm produces a segmentation of spatially connected regions. These candidate regions are then classified as being vessel or not vessel. The method proposed in is based on fuzzy K-median clustering, where the connected regions are detected by applying 12 rotating 16 × 15 matched filters, and the results go into a classifier. The final result is produced by length filtering. Tracking-based methods utilize a profile model to incrementally step along and segment a vessel. Vessel segments, which are shorter than a given threshold or shorter than 30 pixels and with a height-to-width ratio bigger than a given threshold, are removed.

As reviewed in [6] M. Abramoff, M. Garvin, and M. Sonka, Many important eye diseases as well as systemic diseases manifest themselves in the retina. While a number of other anatomical structures contribute to the process of vision, this review focuses on retinal imaging and image analysis. Following a brief overview of the most prevalent causes of blindness in the industrialized world that includes age-related macular degeneration, diabetic retinopathy, and glaucoma, the review is devoted to retinal imaging and image analysis methods and their clinical implications. Methods for 2-D fundus imaging and techniques for 3-D optical coherence tomography (OCT) imaging are reviewed. Special attention is given to quantitative techniques for analysis of fundus photographs with a focus on clinically relevant assessment of retinal vasculature, identification of retinal lesions, assessment of optic nerve head (ONH) shape, building retinal atlases, and to automated methods for population screening for retinal diseases. A separate section is devoted to 3-D analysis of OCT images, describing methods for segmentation and analysis of retinal layers, retinal vasculature, and 2-D/3-D detection of symptomatic exudates-associated derangements, as well as to OCT-based analysis of ONH morphology and shape.

IV. RESULTS

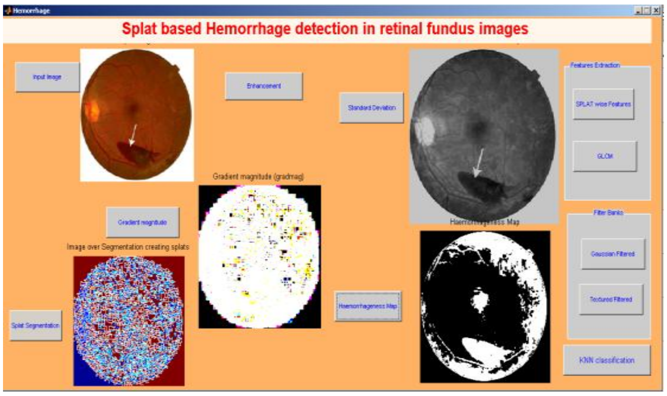

Fig. 2: Get a retinal image from the data

set for the hemorrhage detection. CLAHE operates on small regions in the image, called tiles, rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the histogram specified by the 'Distribution' parameter. The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The strength of intensity discontinuities is often useful for identifying the location of edges in an image. The grad program calculates the magnitude of the intensity gradient (dI/dx, dI/dy) using finite extent convolution masks to estimate the partial derivatives. The splat segmentation is used for extract the region from retinal data which is shows the hemorrhage region identification in fundus image . It will create the image split group based on the pixel probability and weight. The GLCM is created from a gray-scale image. The GLCM is calculates how often a pixel with gray-level (grayscale intensity or Tone). After create the GLCMs, derive several statistics from them using different formulas. These statistics provide information about the texture of an image. After create the GLCMs, derive several statistics from them using different formulas. These statistics provide information about the texture of an image. The standard deviation shows how much variation or dispersion from the average exists. A low standard deviation indicates that the data points tend to be very close to the mean(also called expected value); a high standard deviation indicates that the data points are spread out over a large range of values. A Gaussian blur (also known as Gaussian smoothing) is the result of blurring an image by a Gaussian function. It is a widely used to reduce image noise. Texture filtering or texture smoothing is the method used to smooth textures. Hemorrhage map depends on the threshold value. The value is between 0 to 0.1. White color indicates the hemorrage region. If the pixel value is greater than the threshold value means it turns to white otherwise the color will be black.

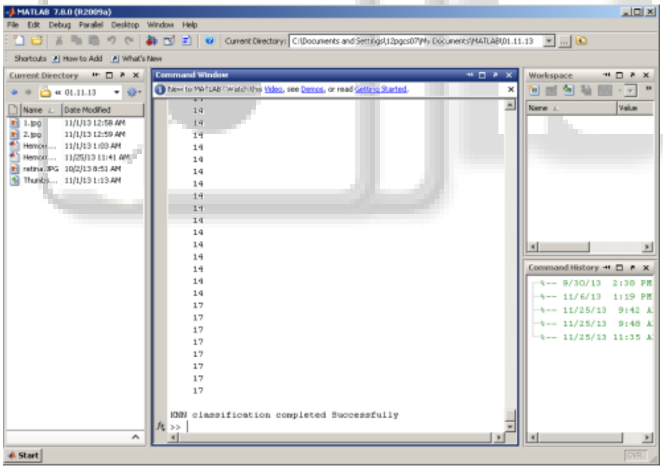

Fig. 3: KNN Classification

An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its k nearest neighbors (k is a positive integer, small). If k = 1, then the object is simply assigned to the class of that single nearest neighbour.

V. CONCLUSIONS AND FURTHER WORK

In this study, I present a splat-based feature classification algorithm with application to large, irregular hemorrhage detection in fundus photographs. Neighboring pixels with similar intensity are grouped into no overlapping splats. A set of features is extracted from each splat to describe its characteristics. These splats are taken as samples for supervised classification in a selected feature space. I present a splat-based feature classification algorithm with application of hemorrhage detection in fundus photographs. 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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