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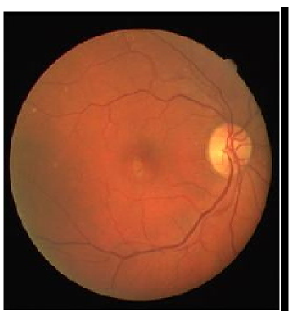
SVM Algorithm for the Robotic Detection of Retinal Hemorrhage in Fundus Images

Dr.K.Sakthivel[1], G.Keerthana[2]
[1]*Professor,* [2]*M.E-Computer Science and Engineering (2nd year)*
Department of Computer Science and Engineering
K.S.Rangasamy College of Technology, Tiruchengode, India

Abstract Many important eye diseases as well as systemic diseases manifest themselves in the retina. Diabetic retinopathy is a vascular disease of the retina which affects patients with diabetes mellitus. A number of other anatomical structures contribute to the process of vision, this paper focuses on retinal imaging and image analysis. Fundus photographs are partitioned into a number of splats covering the entire image. Each splat contains pixels with similar color and close spatial location. A set of distinct features is extracted within each splat. By learning properties of splats formed from blood vessels, a classifier was trained so that it can distinguish blood splats from non-blood splats. Once the blood splats, i.e. vasculature and hemorrhages, are separated from the background, the connected vasculature was removed and the remaining objects considered hemorrhage candidates. The proposed method SVM algorithm determines the origination of the blood vessel network. Finally the segmented image is classified so as to yield normal and abnormal set using Support vector machine.
Index Terms—classification, fundus images, hemorrhage, splat.

I. INTRODUCTION

Diabetic Retinopathy has become a common eye syndrome in most of the developed countries. It leads to damage of the retina, since liquid outflows from blood vessels into the retina. The presence of hemorrhages in the retina is the main symptom of diabetic retinopathy. The number and shape of hemorrhages is used to identify the severity of the disease. Early automated hemorrhage detection can help reduce the existence of blindness. Automated detection of diabetic retinopathy (DR), as used in screening systems, is important for permitting 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 criterion for automated diabetic retinopathy detection. Patients with images that are likely to contain DR are identified and referred for further management by eye care providers. Microaneurysms, exudates, hemorrhages, drusen, cotton wool spot are the main indications of blindness. A retinal hemorrhage is usually analyzed by using a fundus camera in order to detect the inside of the eye. A fluorescent dye is often injected into the patient's bloodstream in advance so the administering ophthalmologist can have a more comprehensive examination of the blood vessels in the retina.



(a)

(b)

Fig. 1. (a) Normal human eye (b) Human eye with hemorrhage.

II. PREPROCESSING

A preprocessing stage is required for improving the image quality prior to the detection stage. The automated system is configured for detection of Hemorrhage in such a way that it can be applied for both the gray level and green layered images. Here, the green plane of the original RGB color image used as red lesions has the highest contrast with the background in this color plane. It is observed that the contrast of the retinal images tends to be bright in the center and diminish at the side. To equalize the image intensity level, is applied (contrast limited adaptive histogram equalization) twice. Then the image histogram is examined and also checked the equalization of the intensity level from 0-255.

III. SPLAT SEGMENTATION

In splat based illustration the image re-sampling approach onto an irregular grid. Background regions, are regular variations in appearance, incline to consist of fewer large splats while foreground consist of smaller splats. At pixel level, the dissemination of hemorrhage pixels and non-hemorrhage pixels are unfair. Since hemorrhages are usually settled for a small fraction of the entire image. Instead of comprising only similar background pixels for training, as many re-sampling methods do, a splat based approach to maximize the variety of training samples by recalling all vital samples foreground regions consist of a large number of smaller splats. Pixels are part of the same object or structure share similar color, intensity and spatial location, the image is partitioned into non-overlapping splats of similar intensity covering the entire image. At pixel level, the distributions of hemorrhage pixels and non-hemorrhage pixels are unfair, since hemorrhages usually account for a small fraction of the entire image. To create splats which preserve preferred boundaries specifically, i.e., boundaries separating hemorrhage from retinal background we perform scale-specific image over segmentation. Due to variability in the advent of hemorrhage, initially aggregate gradient magnitude of contrast enhanced dark bright opponency image at a range of scales for localization of contrast boundaries separating blood and retinal background. Then maximum of these gradient over scale of interest is taken in carrying out watershed segmentation. Assume that scale space representation of image I(x,y;s) with Gaussian kernels Gs at scale of interest s ∈s1,s2........sn, the gradient magnitude $|\nabla I(x,y;s)|$ is computed from its horizontal and vertical derivatives.

$$|\nabla I(x,y;s)| = \sqrt{\mathrm{I}_X(x,y;s)^2 + \mathrm{I}_Y(x,y;s)^2}$$

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

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

Symbol represents convolution and $(\frac{\partial G_s}{\partial x}),(\frac{\partial G_s}{\partial y})$ are first order derivative of Gaussian at scale *s* along horizontal and vertical direction.

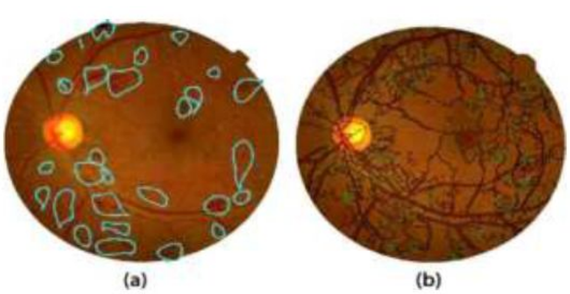


Fig. 2. (a) Pixel based approach (b) Splat based approach.

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IV. FEATURE EXTRACTION

Certain splats with their associated feature vectors and reference standard labels, a classifier can be trained to identify target objects. In this method, two classes of features are extracted for splat–based hemorrhage detection: 1) splat feature aggregated from pixel-based responses; 2) splat wise features (no aggregation is required).

Color within each splat is extracted in RGB color space and dark-bright (db), red-green (rg), and blue-yellow (by) opponency images. In combination, initially, the mean and standard deviation (SD) of filtering response within splat p are calculated. Furthermore, the mean and SD of filtering responses along boundaries of splat p are calculated as additional features of that splat. In addition to splat features aggregated from pixel-based responses, we also extract splat wise features which do not need to be aggregated. Shape features, such as splat area, extent, location and hardness, are derived based on individual splat distribution. Texture features are extracted according to the statistics of gray-level co-occurrence matrix.

V. FEATURE SELECTION

To decrease the dimensionality of feature space by finding relevant features and ignoring those irrelevant or redundant ones. There are two approaches for the feature selection method: a) filter approach b) wrapper approach. The filter filter approach is fast, enabling their practical use on high dimensional feature spaces. b) wrapper approach selects optimal combinations of relevant features are minimized.

To take advantage of both approaches, we use a two-step feature selection process a filter approach followed by a wrapper approach. The appropriate number of features to be retained is determined by reviewing how it differs with the misclassification error (MCE) using cross-validation. Classification is carried out using quadratic discriminant analysis (QDA), which performs likelihood ratio test under the assumption of multivariate normal distributions. The percentages of misclassified splats on the training subset and the testing subset are plotted as a function of increasing numbers of sorted features. Overfitting occurs where the error on the testing subset increases while the error on the training subset decreases. The appropriate number of features is chosen according to the turning point where the smallest MCE on the test set is reached right before overfitting begins to occur. After preliminary selection, irrelevant features are removed. 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.

VI. CLASSIFICATION

After feature selection, a trained SVM classifier is set up in a "calibrated" feature space with a discriminative features. Support vector machine is a supervised learning process applied for analyzing the training data to find an optimal way to classify the diabetic retinopathy images into their respective classes namely Normal, Mild and Severe. SVM is a robust method used for data classification and regression. Soft class labels to query splats based on the labels of their nearest neighbors in the feature space, i.e., those instances in the training set. When neighbors were labeled as being a hemorrhage splat, the posterior probability that the query splat comes from hemorrhage itself was determine. The distance for finding the nearest neighbors is measured with Euclidean metric in the optimized feature space. At the testing stage, the system is fully automatic. The nearest neighbor rule attempts to estimate the a posteriori probabilities from labeled training samples. A large value of is desirable to obtain reliable estimates. But only when all of the nearest neighbors are close enough to the query sample, its a posteriori probability can be approximated by the majority labels of its neighbors. Therefore, a compromise has to be made so that the value of accounts for only a small fraction of the training samples.

VII. CONCLUSION AND FUTURE WORK

The main aim of this work is to reduce the ophthalmologists work in screening the DR based on hemorrhages using SVM classifier. The retinal images are subjected to gray scale conversion, preprocessing and feature extraction steps. The SVM classifier classifies the images as Normal, Mild and Severe based on the extracted features as input. Thus this SVM technique has given a successful DR screening method which helps to detect the disease in early stage. Support vector machine is a supervised learning process applied for analyzing the training data to find an optimal way to classify the diabetic retinopathy images into their

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respective classes namely Normal, Mild and Severe. SVM is a robust method used for data classification and regression.

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