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Research Article

RETINAL HEMORRHAGE DETECTION IN DIABETIC RETINOPATHY USING FNN CLASSIFIER

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ABSTRACT

Automatic detection of diabetic retinopathy used in screening systems. In this research a novel splat feature classification method is proposed for the retinal hemorrhage detection to large irregular hemorrhage detection in fundus images. In proposed method retinal color image segmented into non-overlapping segments and each segment contain information about pixels and their spatial locations. A set of features are extracted from each splat to describe its characteristics relative to its surroundings, employs responses from a variety of filter bank, interacting with neighbor splats and shape and their texture information. An optimal subset of splat features are selected by a filter approach followed by a wrapper approach. A FNN classifier is proposed to train with splat-based expert annotations. To improve classification performance with this work FNN classifier is added instead of KNN[1]. A FNN classifier is proposed to train with splat-based expert annotations. FNN method it is based on pixel classification using a feature vector extracted from preprocessed retinal images and given as input to a neural network. 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.

Keywords: Supervised Classification, FNN, Retinal Hemorrhage, Diabetic Retinopathy, NN

INTRODUCTION

Diabetic retinopathy is the most common diabetic eye disease and it leads to blindness. The changes in the blood vessels of the retina is the main reason, blood vessels may swell and leaks of fluid, new blood vessels which are abnormally grown on the region of the retinal. The retina is the sensitive light tissue at the back of the eye; diabetic retinopathy can get worse and cause vision loss. Both eyes are usually affected by Diabetic retinopathy[1-4]. Different techniques have been designed to detect each type of these lesions separately in DR detection system. Retinal hemorrhages are caused by retinal ischemia and primarily caused by abnormally fragile blood vessels in hypertension. Large hemorrhages are asymptomatic except when they are located in the center of the macula. Large hemorrhages indicate more severe disease, and increasing detection of such lesions will lead to elimination of more severe false negatives. Existing approaches fall into three categories: pixel-based approaches, lesion-based approaches, and image-based approaches. the size of the lesion is yet another important factor to consider in decision making processes of DR detection systems, which is closely related to the severity of disease that need timely treatment. Large hemorrhages occur infrequently, and their appearance is highly variable, making their shape modeling and automated detection a challenge. Detecting DR lesions[5] is often accomplished by supervised classification which involves training of classifiers using expert labeled target objects at pixel level. Features are extracted from each pixel and soft labels are assigned accordingly, indicating the probability of the pixel being one or part of a target object. Abnormal pixels are then combined into objects[7-10].

A disease of the human retina is Diabetic Retinopathy caused by diabetes. It is diagnosed by observing the extent of two different kinds of defects on the retina: (1) Micro-aneurysms are amongst the first signs of the presence of diabetic retinopathy. But, it is important to note that, while a critical component of any DR screening system, detection of micro-aneurysms is not equivalent to detection of DR. The detection of hemorrhages is one of the important factors in the early diagnosis of Diabetic Retinopathy. The existence of hemorrhages is generally used to diagnose DR or hypertensive retinopathy by using the classification scheme of Scheme. In spite of detecting micro-aneurysms, it is difficult for ophthalmologists to find them in non-contrast fundus images. The contrast observed in a micro-aneurysm image is very low; therefore, ophthalmologists usually detect micro-aneurysms, fluorescein angiograms are used. However, it is hard to use fluorescein as a contrast medium for diagnosing all the medical examiners subjected to mass screening micro-aunerysms and (2) regions of capillary non-perfusion.

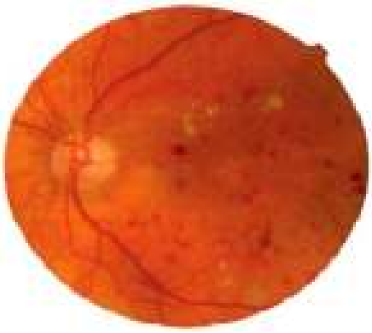

Figure 1: Retinal hemorrhages Image

Detecting DR lesions is often accomplished by supervised classification which involves training of classifiers using expert labeled target objects at pixel level. Features are extracted from each pixel and soft labels are assigned accordingly indicating the probability of the pixel being one or part of a target object. Abnormal pixels are then combined into objects. It is costly to obtain expert labeled reference standards for training and estimate which is exclusive and flat to error. Perfectly preparation samples are planned to be both informative to the classification model and varied so that information provided by individual samples overlaps as smaller as possible. Larger hemorrhages occur rarely, have non regular shape and can occur without accompanying other signs of DR, such as micro-aneurysms or small hemorrhages. They will thus be missed by systems designed to detect the regular DR lesions. Several approaches have been already presented for this purpose using different technique. But they are all of having some deviations or drawbacks in this issues. Large hemorrhages indicate more severe disease, and improved detection of such lesions will lead to elimination of more severe false negatives.

Figure 2: Fundus Image

System Model

Preprocessing

Preprocessing model for the input retinal images. This preprocessing approach is proposed to reduce the imperfections like lighting variations, poor contrast and noise and generate images more suitable for extracting the pixel features demanded in the classification step, a preprocessing comprising the following steps[2] is applied:

1) Vessel central light reflex removal, 2) background homogenization, and 3) vessel enhancement.

Splat segmentation

The image is partitioned into non-overlapping splats of similar intensity covering the entire image. To create splats which preserve desired boundaries precisely, boundaries separating hemorrhages from retinal background, perform a scale-specific image over-segmentation in two steps. Due to the variability in the appearance of hemorrhages, 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. Next, [7]the maximum of these gradients over scale-of-interest (SOI)is taken in performing watershed segmentation. The number of splats in each image is set to be within a limit, which is achieved by thresholding the topographic surface iteratively. The threshold is increased by a constant step until the number of splats is lower than a predefined upper bound. To produce an image level reference standard, images with splat-based annotation from the expert, i.e., images containing hemorrhages are given labels of “1” and the rest are given labels of “0” as they contain no hemorrhage splats. For edge effect removal features are extracted from all of splats, those containing pixels on the circular boundaries of FOV are excluded from further processing.

Feature extraction

To detect hemorrhage feature extraction is based on two categories Pixel-Based and splat based features[2] . In

Figure 3: Splat Segmentation

Pixel based extraction first extracts colors from splats using RGB color space according to its dominant pixel values Hemorrhages suffer from the absolute color of blood regions shows great variability while blood regions and the background exhibit similar color distributions with substantial overlap of their histograms. For sharp edges and soft edges are relative with respect to their underlying scale. The high intensity points and low intensity points evolve towards different directions across the scale space produced by

Gaussian kernels then to find the optimal strategy to aggregate pixel responses within each splat and associate it with a single feature value two approaches are used, resulting in four sets of features. In addition to splat features aggregated from pixel-based responses also extract splat wise features which do not need to be aggregated. Shape features, such as splat area, extent, orientation and solidity, are derived based on individual splat distribution. Texture features are extracted according to the statistics of gray-level co-occurrence matrix (GLCM)[6]. The number of splats in each image is set to be within a limit, which is achieved by thresholding the topographic surface iteratively.

The threshold is increased by a constant step until the number of splats is lower than a predefined upper bound. To produce an image level reference standard, images with splat-based annotation from the expert, i.e., images containing hemorrhages are given labels of “1” and the rest are given labels of “0” as they contain no hemorrhage splats. For edge effect removal features are extracted from all of splats, those containing pixels on the circular boundaries of FOV are excluded from further and Tamura signatures.

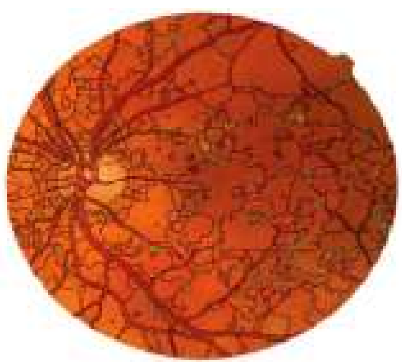

Figure 4: Annotation

2.4 Feature selection

The dataset is partitioned into a training set and a testing set. Feature selection evaluates discrimination power of candidate features according to reference standard labels of training set and comes up with an optimal subset as the input to a classifier. Given reference standard labels, splats in the training subset are grouped into hemorrhage splats and non-hemorrhage splats.

1) Filter Approach the test is applied to each feature of the two groups. The values sorted in ascending order are taken as measures of how effective those features are in predicting the correct labels of splats. The appropriate number of features to be retained is determined by inspecting how it varies with the misclassification error (MCE)[2] using cross-validation. Classification is carried out using quadratic discriminant analysis (QDA)[1], 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. Over fitting 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 over fitting begins to occur.

2) Feature Selection with a Wrapper Approach: 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. A FNN classifier is proposed to train with splat-based expert annotations. FNN method it is based on pixel classification using a feature vector extracted from preprocessed retinal images and given as input to a neural network.

2.5 Fuzzy Neural Network Classification

Fuzzy neural networks (FNNs) for pattern classification usually use the back propagation type learning algorithms to learn the parameters of the fuzzy rules and membership functions from the training data. Fuzzy neural networks (FNNs), which combine the capability of fuzzy reasoning in handling uncertain information. It is based on pixel classification using a feature vector extracted from preprocessed retinal images and given as input to a neural network. Back propagation multilayer neural network (FNN) for vascular tree segmenting, after histogram equalizing, smoothing and edge detection, a multilayer feed forward network, consists of an input layer, three hidden layers and an output layer, are adopted in this paper. The input layer is composed by a number of neurons equal to the dimension of the feature vector. Regarding the hidden layers, several topologies with different numbers of neurons. A number of three hidden layers, each contains 15 neurons, provided optimal NN configuration. The output layer containing a single neuron and is attached, as the remainder units, to a nonlinear logistic sigmoid activation function, so its output ranges between 0 and 1. This choice was grounded on the fact of interpreting NN output as posterior probabilities.

CONCLUSION

In this work presents a splat-based feature classification algorithm with application to large, irregular hemorrhage detection in fundus photographs. Neighboring pixels with similar intensity are grouped into non-overlapping splats. A set of features is extracted from each splat to describe its characteristics relative to its surroundings, employing response from a varing of filter bank, interactions with neighbor splats, and shape and texture details. An optimal subset of splat features are selected by a filter approach followed by a wrapper approach. These splats are taken as samples for supervised classification in a selected feature space. A FNN classifier is proposed to train with splat-based expert annotations. FNN method it is based on pixel classification using a feature vector extracted from preprocessed retinal images and given as input to a neural network. 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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