STUDY AND ANALYSIS OF AN OPTIC DISC THROUGH LOCAL BINARY PATTERNS

U. Lenin Marksia
Assiatant Professor/ECE
Dr. Sivanthi Aditanar College of Engineering

Abstract

In this paper, we investigates the capabilities in the texture of fundus image to differentiate between ical and healthy image. We purpose a new descriptor for texture classification that is robust to image blurring. The descriptor utilizes phase information computed locally in a window for every image position. Here local binary patterns (LBP) used as a texture descriptor for retinal image has been explored and compared with other descriptors such as LBP filtering and local phase quantization. The goal is to identify diabetic retinopathy (DR) at earlier stage. The algorithm allows to automatically segment the optic disk and blood vessels from a fundus image to facilitate the early detection of certain pathologies and to fully automate the process for extraction of optic disk contour is mainly based on mathematical morphology and blood vessel extraction based on fuzzy logic. Also the resultant image is to be transferred through mail.

I. INTRODUCTION

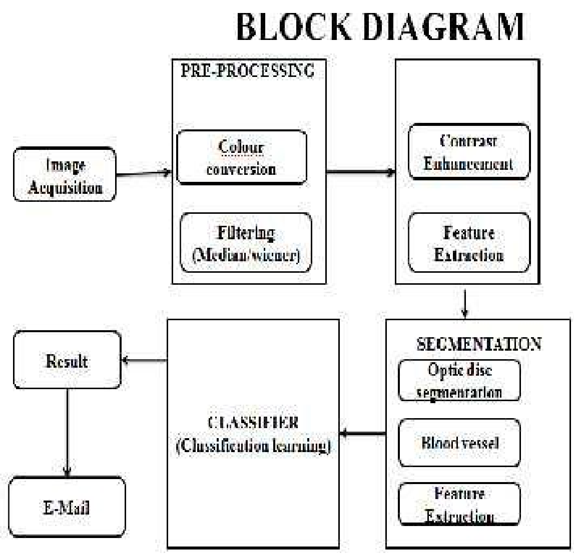
The world health organization estimated that 253 million people live with vision impairment:36 million are blind and 217 million have moderate to severe vision impairment .81% of people ho are blind or have moderate or severe vision impairment are aged 50 years and above. Nowadays more number peoples are affected by diabetics due to change in food culture .Initially this non-contagious disease affect the vision of the person particularly in a retinal layer of eye, later it losses the vision. Here diabetic retinopathy (DR) is stressed as a major one because later on rectification become tedious. Only the initial recognition helps to prevent the defect. Based on their obvious manifestations during DR progression, micro vascular lesions have been utilized as the major criteria for evaluating and classifying the retina in DR. However, diabetes-induced changes also occur in nonvascular cell types that play an important role in the development and progression of DR, albeit in unison with the vasculature. DR falls into 2 broad categories: the earlier stage of nonproliferative diabetic retinopathy (NPDR) and the advanced stage of PDR. Classification of NPDR is based on clinical findings manifested by visible features, including microaneurysms, retinal hemorrhages, intraretinal microvascular abnormalities (IRMA), and venous caliber changes , while PDR is characterized by the hallmark feature of pathologic preretinal neovascularization . While these visible features of DR provide useful measures for detection and diagnosis, improving technology has enabled the detection of more subtle pathologies such as retinal function deficits and neural layer abnormalities in patients . An important additional categorization in DR is diabetic macular edema (DME), which is an important manifestation of DR that occurs across all DR severity levels of both NPDR and PDR and represents the most common cause of vision loss in patients with DR. DME arises from diabetes-induced breakdown of the blood-retinal barrier (BRB), with consequent vascular leakage of fluid and circulating proteins into the neural retina . The extravasations of fluid into the neural retina leads to abnormal retinal thickening and often cystoid edema of the macula. Many systemic features of diabetes influence DR.

For example, Dyslipidemia and hypertension may also influence DR , although in the context of individual patients, the associations between plasma lipids, lipoproteins, and DR are not sufficiently strong to define retinopathy risk. Likewise, hypertension has been linked to increased risk of DR , and some data indicate that patients may benefit from the use of antihypertensive agents . However, recent studies have demonstrated that more intensive blood pressure control does not confer additional benefits on retinopathy progression compared with standard control . Taken together, optimization of systemic risk factors is clearly important; however, even hyperglycemia (as measured by HbA1c) may only account for around 10% of DR risk , and hypertension and dyslipidemia combined may carry <10% risk in some cohorts . Such data strongly suggest that additional unidentified factors also play critical roles in DR initiation and progression.

It investigates discrimination capabilities in the texture of fundus to differentiate between pathological and healthy images. In particular, the main focus lies in exploring the performance of local binary patterns (LBP) as a texture descriptor for retinal images. The LBP technique has been given a lot of attention in recent years [3], [4]. It is based on looking at the local variations around each pixel and assigning labels to different local patterns. Thereafter, the distribution of the labels is evaluated and used in the classification stage. There are many examples of the success of LBP used to describe and classify textures in general and also in the case of medical imaging . However, regarding fundus image processing, LBP have not been widely used. Most state-of-te-art works that use the LBP technique on fundus images focus on the segmentation of the retinal vessels rather than on a full diagnosis system, although some examples can be found in this direction . In , abnormal signs were extracted from fundus images to detect normal fundus and two DR stages. Thirteen features, such as area of hard exudates, area of blood vessels, bifurcation points, texture and entropies, fed three different classifiers [probabilistic neural network (PNN), Decision Tree C4.5, and support vector machine (SVM)]. The texture is found by LBP and Laws energy. A previous segmentation of the exudates, optic disc, and blood vessels is needed for feature extraction. The experiments are conducted on 156 subjects, and the PNN is chosen as the best classifier with threefold cross validation (CV) . In more recent work of Mookiah et al. , a different methodology for AMD characterization is done through local configuration patterns (LCP) rather than by LBP. Linear configuration coefficients and pattern occurrence features are extracted, and a linear SVM is used after feature selection. Krishnan and Laude combine LBP with entropies and invariant moments to generate an integrated index for DR diagnosis. They demonstrated that there exist significant differences in the index for normal images and DR images, and they emphasized that lesion segmentation was not required . Garnier et al., deal with the AMD detection using LBP. The texture information on several scales is analyzed through a wavelet decomposition and an LBP histogram is found from the wavelet coefficients. Linear discriminant analysis (LDA) is used for feature dimension reduction using the values of the entire LBP histogram as input features. Image classification on a set of 45 images is evaluated with a leave-one-out validation method The goal of this paper is to distinguish between DR, AMD, and normal fundus images at the same time and avoiding any previous segmentation stage of retinal lesions. The texture of the retina background is directly analyzed by means of LBP, and only this information is used to differentiate healthy patients and these two pathologies. A comprehensive study about what type of classifier obtains the best results is also undertaken. The performance of logistic regression, neural networks, SVM, naive Baye’s, J48, rotation forest, random forest, and AdaBoost M1 is compared. This approach is different from previous works that use LBP. Mookiah et al. require the segmentation of exudates in addition to segmentation of main structures (optic disc and vessels) for feature extraction, and although three different classes are identified, they only focus on DR detection. Krishnan and Laude and Garnier et al. do not need previous segmentations but only handle with a disease at time, in particular with DR and AMD diagnosis, respectively. Moreover, Krishnan and Laude did not provide values to determine the accuracy of the normal and DR discrimination. Many operators for texture description have been defined in the literature. Some of them are modifications of the original

LBP such as completed LBP , LBP filtering (LBPF) , dominant LBP , etc. Other state-of-the-art descriptors are completely different as Weber local descriptor , LCPs , or local phase quantization (LPQ) . The LBP have been seen to be useful in many applications and is simple and easy to compute. For these reasons, we wanted to explore LBP for the present application. For comparison, experiments using LBPF and LPQ are presented as well. The rest of the paper is organized as follows: In Section II, materials and methods are described, and in Section III, the proposed method is presented. Section IV shows how system validation was performed, as well as the obtained results. Finally, Section V provides discussion, and Section VI presents conclusions and some future areas for work.

II.METHODOLOGY



A .Local Binary Pattern:

LBP was introduced for texture classification, later it was used for face recognition and so on. In early stage image is divided into several sized window and represented as the combination of LBPH features for all window later ,the LBPH feature with various sizes and location are used as week classifier for which JS boosting is used to learn a recognition classifier.LBP are a powerful gray scale texture operation used in many computer vision application because of its computation simplicity. The LBP feature vector, in its simplest form, is created in the following manner:

Divide the examined window into cells(eg: 16x16 pixels or 3x3 pixels for each cell)

For each pixel in a cell, compare the pixel to each of its 8 neighbors(on its left-top, left-middle, left-bottom, right-top, etc).Follow the pixels along a circle, i.e. clockwise or counter clock wise

Where the center pixel’s value is greater than the neighbor’s value, write “0” . Otherwise, write “1”.

This gives an 8 digit binary number

Compute the histogram, over the cell, of the frequency of each ‘number'. This histogram can be seen as a 256-dimensional feature vector.

Optionally normalize the histogram

Concatenate histogram of all cells. This gives a feature vector for the entire window.

III.PROPOSED METHOD

Pre-processing is a common name for operations with images at the lowest level of abstraction — both input and output are intensity images. These iconic images are of the same kind as the original data captured by the sensor, with an intensity image usually represented by a matrix of image function values (brightnesses). The aim of pre-processing is an improvement of the image data that suppresses unwilling distortions or enhances some image features important for further processing, although geometric transformations of images (e.g. rotation, scaling, translation) are classified among pre-processing methods here since similar techniques are used.

The image pre-processing is the process in which images is subjected through various filtering technique in order to give noble results. The image enhancement starts with smoothing. The aim of image preprocessing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for feature processing.

Brightness transformation modify pixel brightness this transformation depends on the property of pixel itself

1.Brightness corrections.
2.Grayscale transformation.

1.Brightness correction:
i)Considers original brightness
ii)Pixel position in the image

2.Grayscale transformation:
i)Change brightness without regard to position in the image (i.e)it is does not depends on the position of the pixel in the image. q=T(p)

a) IMAGE FILTERING:
Image filtering can be grouped in two depending on the effects:

Low pass filters(Smoothing)
Low pass filtering (aka smoothing), is employed to remove high spatial frequency noise from a digital image. The low-pass filters usually employ moving window operator which affects one pixel of the image at a time, changing its value by some function of a local region (window) of pixels. The operator moves over the image to affect all the pixels in the image.

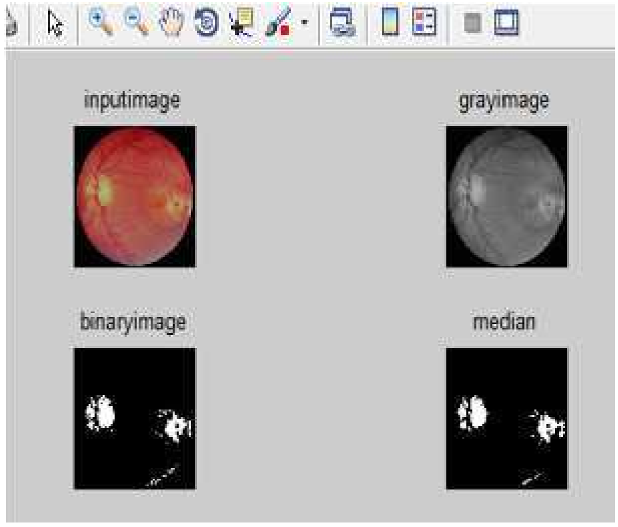
High pass filters (Edge Detection, Sharpening)
A high-pass filter can be used to make an image appear sharper. These filters emphasize fine details in the image - the opposite of the low-pass filter. High-pass filtering works in the same way as low-pass filtering; it just uses a different convolution kernel. When filtering an image, each pixel is affected by its neighbors, and the net effect of filtering is moving information around the image.

i)MEDIAN FILTER:
The median filter is a non-linear digital filtering technique, often used to remove noise from an image or signal. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example edge detection on a0n image).It is widely used in image processing because under certain conditions, it preserves edges while removing noise. Digital filter is nothing but is an 2 dim-array of real numbers.2-D image is divided into N-rows and M-columns. Each rows and columns called as an pixels. It is classified in to three types

1. Binary image(Black and white) {0's and 1's}
Gray scale image {0 to 255}
Color image{RGB}

GAUSSIAN NOISE:
Gaussian noise is caused by random fluctuations in the signal. Its modeled by Random values added to an image.

SALT AND PEPPER NOISE:
Its also knows an impulse noise. This noise can be caused by sharp and sudden disturbance in the image signal. Its appearance is randomly scattered white or black pixel over the image.



WIENER FILTER
The goal of the Wiener filter is to filter out noise that has corrupted a signal. It is based on a statistical approach. Typical filters are designed for a desired frequency response. However, the design of the Wiener filter takes a different approach. One is assumed to have knowledge of the spectral properties of the original signal and the noise, and one seeks the linear time-invariant filter whose output would come as close to the original signal as possible. Wiener filters are characterized by the following:

Assumption: signal and (additive) noise are stationary linear stochastic processes with known spectral characteristics or known autocorrelation and cross-correlation .

Requirement: the filter must be physically realizable/causal.

Performance criterion: minimum mean-square error (MMSE).

IMAGE ENHANCEMENT:
The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers. This is

completely a subjective process. It accentuates or sharpens image features such as edges, boundaries, or contrast to make a graphic display more helpful for display and analysis. Filtering is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image. In this we have to define eight masks in eight directions (North, South, East, West, NE, SE, SW and NW).After sliding of each mask in its particular direction only centre pixel is modified preserving the other pixels and hence preserving the edges.

IV.IMAGE SEGMENTATION:

Image segmentation is the process of partitioning an image into different meaningful regions. Here Watershed algorithm is implemented for the purpose of segmentation. Watershed technique is a powerful method of image segmentation with high success rate. Here segmentation is to be classified in to two type i)optic disk segmentation, ii)blood vessel segmentation

1.WATERSHED METHOD

This method is used to visualize an image topographically in 3D. There are three types of points. In the study of image processing, a watershed is a transformation defined on a grayscale image. The name refers metaphorically to a geological watershed, or drainage divide, which separates adjacent drainage basins. The watershed transformation treats the image it operates upon like a topographic map, with the brightness of each point representing its height, and finds the lines that run along the tops of ridges.

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 ima ge processing primarily for segmentation purposes.

watershed segmentation follows this ba sic procedure:

Compute a segmentation function. This is an image whose dark regions are the objects you are trying to segment.

Compute foreground markers. These are connected blobs of pixels within each of the objects.

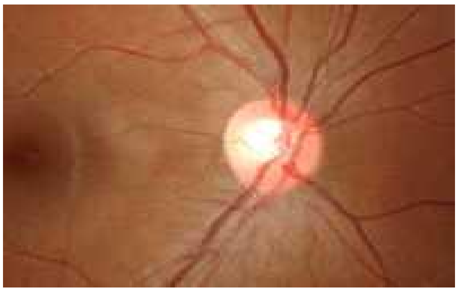
Compute background markers. These are pixels that are not part of any object.

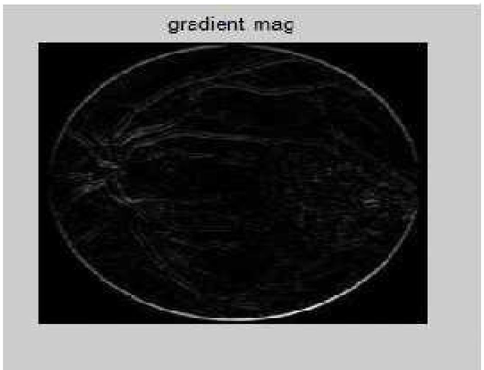
Modify the segmentation function so that it only has minima at the foreground and background marker locations.

Compute the watershed transform o f the modified segmentation function.

a) OPTIC DISK SEGMENTATION

The optic disc or optic nerve head is the point of exit for ganglion cell axon leaving the eye. Because there are no rods or cones overlying the optic disc, it corresponds to a small blind spot in each eye. The ganglion cell axons form the optic nerve after they leave the eye. The optic disc represents the beginning of the optic nerve and is the point where the axons of retinal ganglion cells come together. The optic disc is also the entr y point for the major blood vessels that supply the re tina The optic disc in a normal human eye carries 1–1.2 million afferent nerve fibers from the eye towa rds the brain image of a healthy optic disc in a 24-ye ar-old female.





BLOOD VESSEL SEGMENTATION:
FUZZY LOGIC:

Fuzzy logic is a form of many-valued logic in which the truth values of variables may be any real number between 0 and 1. It is employed to handle the concept of partial truth, where the truth value may range between completely true and completely false.By contrast, in Boolean logic, the truth values of variables may only be the integer values 0 or 1.

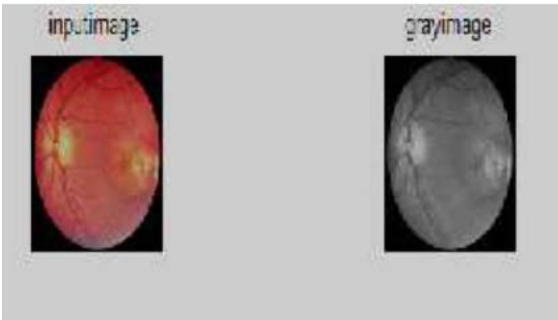
OPERATION:

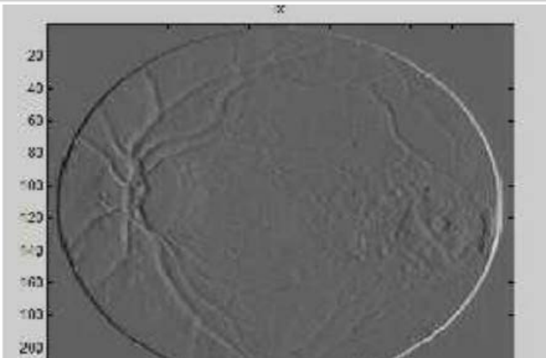
Fuzzy logic works with membership values in a way that mimics Boolean logic.

EDGE DETECTION:

Edge detection includes a variety of mathematical methods that aim at identifying points in a digital image at which the image brightness changes sharply or, more formally, has discontinuities. The points at which image brightness changes sharply are typically organized into a set of curved line segments termed edges. The same problem of finding discontinuities in one-dimensional signals is known as step detection and the problem of finding signal discontinuities over time is known as change detection. Edge detection is a fundamental tool in image processing, machine vision and computer vision, particularly in the areas of feature detection and feature extraction.

OUTPUT:





CONCLUSION

In this paper, a new approach for AMD and DR diagnosis was presented. It is based on analyzing texture discrimination capabilities in fundus images to differentiate healthy patients from AMD and DR images. The performance of LBP along with different classifiers was tested and compared with other texture descriptors. The most important finding is that the proposed method is capable of discriminating the classes based on analyzing the texture of the retina background, avoiding previous segmentation of retinal lesions. Such lesion segmentation algorithms might be both time consuming and potential inaccurate, thus avoiding the segmentation is beneficial. The obtained results demonstrate that using LBP as texture descriptor for fundus images provides useful features for retinal disease screening. In future work, a larger test of the method with more images should be done. Moreover, some work should be carried out to develop strategies that enable the analysis of the type of images that were excluded from the initial database, such as tessellated fundus, images with highlights or typical artefacts. Other research line is to automatically determine the presence of biological image variation (tessellation, highlighting or other) prior to the classification step to train different classifiers and use different feature combinations for each specific case. We also wish to explore more texture descriptors. For example, the idea of LBP has been developed further into nonbinary coding for texture description and has provided good results recently [47]. In addition, recent literature describes new texture descriptors based on the co-occurrence method with promising results used on medical image.

REFEREANCES

World Health Organization (WHO), “Universal eye health: a global action plan 2014–2019,” 2013.

World Health Organization (WHO), “Action plan for the prevention of avoidable blindness and visual impairment 2009–2013,” 2010.

T. Ojala, M. Pietikinen, and T. Menp, “A generalized local binary pattern operator for multiresolution gray scale and rotation invariant texture classification,” in Proc. 2nd Int. Conf. Adv. Pattern Recog., 2001, pp. 397–406.

T. Ojala, M. Pietikainen, and T. Maenpaa, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,”IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 7, pp. 971–987, Jul. 2002.

T. Ahonen, A. Hadid, and M. Pietikainen, “Face description with local binary patterns: Application to face recognition,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 12, pp. 2037–2041, Dec. 2006. [6]

M. Heikkil,M. Pietikinen, and C. Schmid, “Description of interest regions with local binary patterns,” Pattern Recog., vol. 42, no. 3, pp. 425–436, 2009