TEST Engineering & Management

July – August 2020
ISSN: 0193-4120 Page No. 110- 114

Glaucoma Detection: An approach using hybrid texture feature descriptors

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Article Info
Volume 83
Page Number: 110- 114
Publication Issue:
July - August 2020

Article History
***Article Received**: 06 June 2020*
***Revised**: 29 June 2020*
***Accepted**: 14 July 2020*
***Publication**: 25 July 2020*

Abstract

In this paper, we proposed Glaucoma detection in images using a hybrid texture-based Local Binary Pattern (LBP) and Grey Level Co-occurrence Matrix (GLCM) feature descriptors. The significant features are extracted from LBP, GLCM, and LBP+GLCM. Finally, significant features are used with the Support Vector Machine (SVM) classifier for Glaucoma detection. The proposed hybrid texture features descriptors method are used RIM2 dataset for the experimentation and empirical results show that the proposed LBP+GLCM hybrid feature descriptors are efficient than other states of the art techniques.

Index Terms—LBP, GLCM, Optic Disc, Optic Cup, Intraocular Pressure, retina.

1. INTRODUCTION

Glaucoma is a chronic neurological disorder that occurs in the eye due to gradual degradation of the optic nerve leading to complete vision loss. Detection of glaucoma at an early age is difficult due to the absence of symptoms. Termination of the optic nerve is called an optic nerve head or optic disc. The optic nerve functions as a visual carrier by transferring the visual information from the retina to the visual centres of the brain. Damaged to the optic nerve is due to increased eye's intraocular pressure. Improper functioning of the eye's drainage channel results in the increased intraocular pressure. Increased pressure initially affects the peripheral vision and then the central vision. Loss of central vision leads to complete blindness Loss of vision occurs slowly and gradually and can be controlled, if diagnosed early. Progression of the disease is slow without any symptoms and hence, it is known as the "silent thief of sight". It has been declared by the World Health Organization, that glaucoma contributes to the second leading cause for blindness across the globe. Being a symptomless disease, early detection of glaucoma is not simple because intraocular pressure increases without any pain. To a certain extent, the progression of glaucoma can be limited if accurate and timely detection of disease is done. Humans with any age group are at the risk of such a threatening disease and need to immediately consult the ophthalmologist if any sight-related problems occur. Computer-aided diagnosis (CAD) of glaucoma can be an aid to the ophthalmologist in developing countries in the coming years and aims at preventing blindness across the globe. The structural changes in the optic disc due to increased eyes intraocular pressure is the vital clinical indicator of this eye disease. The optic disc includes the optic cup and is the region of high intensity in the retinal colour fundus images. The intensity in the case of glaucomatous images will be greater than the normal images as a result of the depression of the optic cup. The structural changes occur in the optic disc due to the cupping effect. The proposed work focuses mainly on the extraction of the texture descriptor features such Local Binary Pattern (LBP) which gives spatial structure information of an image and Grey Level Co-occurrence Matrix (GLCM) which can be vital factors in the detection of Glaucoma.

2. RELATED WORKS

A. State of the Art

In the analysis of retinal images, several automated methods for the detection of glaucoma already exist which include several tasks such as pre-processing, segmentation of eye components such as optic disc and optic cup, removal of retinal blood vessels and post-processing. Ahmad et al. [1] used thresholding followed by morphological operations for noise and vessel interference removal. The green plane of the RGB domain of the cropped pre-processed image was used for the detection of the optic cup. The extraction of the Value plane from the HSV domain was used for optic disc detection. Classification of images as glaucomatous or healthy is done based on CDR and ISNT rule. Dutta et al. [2] used double thresholding to extract the super pixels for the segmentation of background from ROI. A Hough transform for estimate cup and disc boundary is used for calculation of the radius of both optic disc and optic cup. The identification of glaucoma was based on the vertical ratio of the cup to disk. Noor et al. [3] deployed morphological operations such as dilation and erosion for removal of vascular followed by the use of fuzzy clustering segmentation to segment optic disc and optic cup from the extracted region of interest. Some of the existing automated methods include other tasks such are extraction of features from the colour fundus retinal images. Akram MU et al. [4] form a feature vector that consists of features such as spatial features and spectral features which are extracted from the region of interest consisting of the pre-processed optic disc. The feature vector also included structural features such as cup to disc ratio, rim to disc ratio. A novel multivariate medoid based classier is modelled for accurate glaucoma detection. The performance of the proposed system is tested using local and publicly available databases consisting of a total of 554 images. Performance of the proposed method for optic disc detection and classifier outperformed the existing state of the art methods and classifiers. Salam et al. [5] use a combination of structural features such as cup to disc ratio and non-structural features such as textural features and intensity features extracted from the fundus images obtained from a local database consisting of 100 images. The uniqueness of the proposed method includes the removal of any conflict in the decision from structural and non- structural features by the introduction of a suspect class. Tehmina Khalil et al. [6] uses unique features which are a combination of robust structural features and textural features in addition to novel proposed features based on super pixels for optic cup detection. The features are divided into two modules namely the hybrid structural feature-set (HSF) and hybrid texture feature-set (HTF) and classified using Support Vector Machine Classifier with the introduction of suspected class for any conflict in the results of both the module. All of these approaches based on the changes in the shape of the regions of the eye require a valid and accurate segmentation of the optic disc which is the region of interest in colour fundus images. However, techniques based on segmentation have one significant drawback: small errors in segmentation may lead to a more significant change in the measurements of the clinical indicators and thus the estimation and diagnosis of glaucoma.

B. Our Approach

An automated system for glaucoma detection based on textural features is developed using the retinal colour fundus images. The technique proposed is based on an evaluation of textural features extracted from retinal fundus images and is independent of segmentation and outlining of the optic disc and optic cup as required in existing automated techniques for glaucoma detection. This proposed work shows the influence of hybrid image-based features on the accuracy and classification of glaucoma from fundus images. The different textural features analysed are Local Binary Pattern features and features extracted from the Grey Level Co-occurrence Matrix. The Support Vector Machine is used for the classification of retinal colour fundus images.

3. PROPOSED METHOD

The proposed method for the detection of glaucoma is based on Local Binary Pattern and the Grey level co-occurrence matrix (GLCM) feature descriptors. The significant features are extracted from LBP, GLCM, and LBP+GLCM. The images obtained are from the RIM-ONE dataset. The images are of varying sizes and resized to 250X250 pixels before the extraction of features. The block diagram of the proposed method is shown in Fig 1.

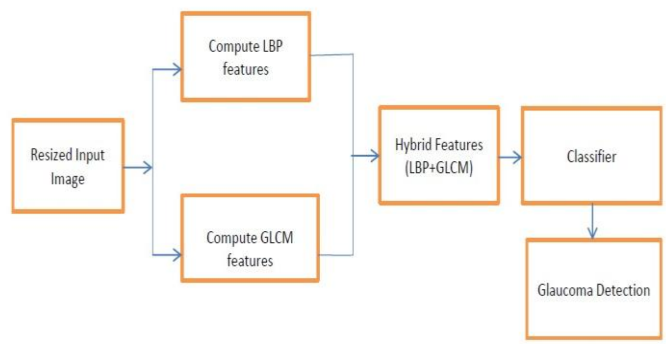

Fig. 1. Block Diagram of the Proposed Method

A. Local Binary Pattern (LBP)

Ojala et al. [7] were the first to introduce LBP operator and this operator based on textural properties is considered as a vital and robust feature for texture classification. LBP is known to be a non-parametric operator. The spatial structure information of an image is described by the LBP operator. LBP was originally designed for a description of the texture. LBP is a simple and yet highly efficient texture operator. It has fast computation and simple utilization, which makes it's a wide usage in many image processing applications. Due to its highly descriptive power and simplicity in its computation, the LBP texture operator has become the most common and popular approach in various image processing applications. LBP operator is very robust to monotonic grey scale changes caused, for instance, variations in illumination and its

July – August 2020
ISSN: 0193-4120 Page No. 110- 114

simplicity in computation have been the major driven force for analysing images in challenging real-time applications. LBP operator is an image operator which performs a transformation of an image into an array of integer labels. These labels describe small scale appearance (textures) of an image. LBP operator labels each pixel of an image by thresholding the neighbourhood of each pixel and considers the results as a binary number for every neighbourhood kernels. The labels directly or their statistics are used for further analysis. Fig 2 illustrates LBP's basic operation. Despite its advantages, this texture operator has a limitation. As it is invariant to rotations and an increase in its computational complexity varies its performance evaluation with feature size increasing exponentially with the number of neighbourhood kernels. LBP fails to capture dominant features in the neighbourhood in case of a larger matrix. The LBP has a limitation towards statistical information as only the pixel difference is used while ignoring the magnitude.

B. Grey Level Co-Occurrence Matrix (GLCM)

The statistical measures described in our study so far are easy to calculate. They do not provide any information about

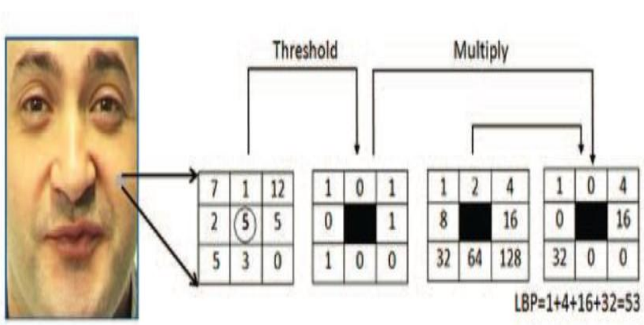

Fig. 2. Illustrates the basic operation of local binary patterns

the repeating nature of texture in the images. The use of these textural features is motivated by the fact that the intensity of the optic cup is usually more than the intensity of the optic disc in a glaucomatous eye as a result of the change in the optic cup area. Texture features can be used to describe the region in an image as the colour features are not sufficient to identify because of the similar histograms. A Grey Level Co-occurrence Matrix (GLCM) is one of the most important measures for images. It can be used to describe the texture for the classification of images. A grey-level co-occurrence matrix (GLCM) is a matrix that contains information about the positions of pixels having similar grey level values. A co-occurrence matrix is a two-dimensional array, P, in which both the rows and the columns represent a set of possible image values. A GLCM Xd [i, j] is defined by first specifying a displacement vector d = (dx, dy) and counting all pairs of pixels separated by d having grey levels i and j. The GLCM is defined by Xd [i, j]= n i, j, where, ni, j is the number of occurrences of the pixel values (i, j) lying at distance, d in the image. The co-occurrence matrix Xd has dimension nn, where n is the number of grey levels in the image. The properties namely Energy, Correlation, Contrast, and Homogeneity are been calculated using the normalized GLCM.

The Contrast property is used to measure the local variations in the GLCM. It is also referred to as variance inertia. The whole image's intensity between a pixel and its neighbour is measured by it. And it range is measured as Range = [0 (size (GLCM, 1) -1) ^{2}] and 0 is for constant image. The equation
is,

$$\sum_{(i,j)} |i-j|^2 P_{(i,j)} \qquad (1)$$

The Correlation measure the occurrence of the specified pairs of the pixels of the joint probability (correlate to the neighbour of its pixel over the entire images). It is NaN for the constant image and 1 and -1 for the positive and negatively correlated image. (I.e. Range = [-1 1]). The equation is,

$$\sum(i,j) = \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i \sigma_j} \qquad (2)$$

Energy is a property used to measure the sum of squared elements. Also referred to as angular second moment or uniformity. Its value is 1 for constant image, otherwise ranges from 0 to 1. (i.e. Range = [0 1]). The equation is,

$$\sum_{(i,j)} P(i,j)^2 \qquad (3)$$

The Homogeneity evaluates the nearness of the distribution of the elements diagonally in GLCM. For diagonal elements its value is 1, otherwise its in between 0 and 1 (i.e. Range = [0 1]). The equation is,

$$\sum(i,j) = \frac{p(i,j)}{1+|i=j|} \qquad (4)$$

C. Hybrid Feature (LBP+GLCM) Descriptors

The LBP has a limitation towards statistical information as only the pixel difference is used while ignoring the magnitude. The statistical measures described in our study are simple and easy to calculate. They do not provide any sort of information about the repeating nature of texture. The use of textural features is motivated by the fact that the intensity of the optic cup is normally higher than the intensity of the optic disc in a glaucomatous eye as a result of the change in the optic cup area. Texture features can be used to describe the region in an image as the colour features are not sufficient to identify because of the similar histograms.

D. Classification

Support Vector Machine (SVM) is used for the classification of colour fundus images in our proposed method. SVM classifies the data points between different classes using the decision boundary which is a hyper plane. Extreme data points from each class are called Support Vectors. SVM tries to find the best and optimal hyper plane which has a maximum margin from each Support Vector. SVM was initially proposed for the linear classification and later kernel methods are introduced by extending to the case of non-linear classification by mapping inputs into high dimensional feature space. SVM is relatively memory efficient and if the margin of separation between the classes is clear, the working of the SVM classifier will be relatively well.

E. Post-Processing

The process of post-processing used in this proposes method is required to reduce the false-positive rate. The only temporal post-processing proposed is used to reduce the spurious and intermittent false alarm rate. [8]

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

The proposed system in our study uses hybrid textural features namely LBP and GLCM and SVM classifier for the detection of glaucoma. The LBP and GLCM features are extracted and the experiment is carried out using two-cross fold to compute the discrimination power.

TABLE I A COMPARATIVE STUDY WITH DIFFERENT FEATURES FOR GLAUCOMA DETECTION

DATABASE USED	FEATURES USED	CLASSIFIER USED	ACCURACY
RIM-ONE	LBP	SVM	89
RIM-ONE	LBP	SVM	86.5
RIM-ONE	LBP	SVM	87.75

A. RIM-ONE DATASET

RIM-ONE is an open retinal image database consisting of colour fundus images available online for analysis of optic nerve head and detection of glaucoma [9]. Several versions of this database exist RIM-ONE r1, RIM-ONE r2, and RIM-ONE r3. These retinal image databases were created by ophthalmologists from the Department of Ophthalmology, Hospital in Spain at the University of Canarias. The version of this database used in our study is RIM-ONE r1 which contains a set of 169 retinal fundus images with annotations for both optic disc and optic cup by five experts in ophthalmology. The retinal images are stored in an RGB colour bitmap format. The images in the dataset are classified as 12 early glaucomas, 14 deep glaucomas, 14 moderate glaucoma, 11 ocular hypertension (OHT) and 118 normal eyes (non-glaucomatous). Each image has been provided with a gold standard from the contours demarcated by five experts. Database available at http://medimrg.webs.ull.es/research/retinal-imaging/rimone/4.2

B. EXPERIMENTAL SETTING

Table 1: shows a comparative study with different features for glaucoma detection. Table 2: shows a comparative study with different feature approach for glaucoma detection

C. RESULTS AND ANALYSIS

The image-based method used in this study for automatic glaucoma detection has been tested over a publicly available database consisting of around 169 images out of which 118 are normal images and 51 are glaucomatous images. The experiment is carried out using a two-cross fold. The 85 images are used for training and 84 images are used for testing for the first experiment and the 84 images are used for training and 85 images are used for testing for the second experiment. The features are extracted in each experiment and then accuracy based on both the isolated features and hybrid features is calculated and then averaged. Post Processing is done prior to calculation of accuracy in each experiment followed by averaging it to obtain the final accuracy of the proposed method giving an overall accuracy of 87.75 %.

5. CONCLUSION

In our work, we have presented an automated glaucoma classification system using retinal fundus images. It is directly based on the images and does not involve any segmentation

TABLE II A COMPARATIVE STUDY WITH DIFFERENT FEATURE APPROACH FOR GLAUCOMA DETECTION

REFERENCE	DATABASE USED	FEATURES USED	ACCURACY
Ruediger Bock et.al[9]	Local Database 200 images	PCA on intensities, textures,FFT. Histogram model LDA on intensities Feature Merging+ 2-stage Classification	86 %

Proposed Method	RIM-ONE Database 169 Images	LBP GLCM LBP+GLCM +temporal post -processing	87.75 %

based measurements. It uses the image-based features for glaucoma recognition. We evaluated LBP, GLCM, LBP+GLCM image-based features. SVM classifier and post-processing are done and an accuracy of 87.5% is achieved. The hybrid features (LBP+GLCM) identified by this method could help the medical experts for detecting glaucomatous eyes and hence used in mass screening.

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