

COMPLEX TEXTURE FEATURES FOR GLAUCOMA DIAGNOSIS USING SUPPORT VECTOR MACHINE

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Abstract - In this paper, Gray Level Co-occurrence Matrix (GLCM) features are effectively utilized for glaucoma diagnosis. Early diagnosis of glaucoma is important to protect vision loss. The proposed system uses four GLCM features such as Contrast, Correlation, Energy, and Homogeneity for the diagnosis. In order to effectively use these features for glaucoma detection they are extracted using the optical density transformed fundus image along with the original features. The classification of fundus image into normal or abnormal is obtained by the Support Vector Machine (SVM) classifier. An internal database of 200 images is utilized for the performance analysis. The results show that the proposed approach helps the ophthalmologists to make their decision very accurately. The proposed system provides 95% classification accuracy.

Keywords - Glaucoma, colour fundus image, GLCM, SVM classifier, Optical density image.

1. Introduction

The assessment of retinal images particularly in fundus images has become increasingly important for the diagnosis of several diseases such as glaucoma, hypertension, cardiovascular disease, and diabetes etc. As fundus images show the pathological changes of retinal vasculatures visibly, they are captured regularly during retinal examinations in order to diagnose the progression of a range of eye diseases. The human assessment of retinal vessels and the detection of abnormalities in the captured

images is a skilled time consuming task. For population based diagnoses of various eye diseases, computer aided diagnosis is seen as an important tool that could detect the changes in retinal images and hence aid in treating the disease at an early stage.

The assessment of glaucoma using optic disc and optic cup segmentation from monocular colour retinal images is presented in [1]. In multidimensional feature space, the information of local image is integrated around each point of interest for OD segmentation. For cup segmentation, the region of support concept is used to detect vessel bends. Then, the right scale is selected automatically for examination. An approach to detect multiple applicant regions of optic disc from fundus image using optic disc localization and segmentation technique is presented [2]. The hybrid features are extracted based on blood vessels and intensity to every applicant region which are finally fed to the classifier stage using SVM classifier.

The diagnosis of glaucoma using empirical wavelet transform and correntropy features are extracted using fundus image is described in [3]. The image is decomposed using empirical wavelet transform for obtaining different frequency bands. Then, correntropy features are extracted and are given as input to the classifier.

Least squares SVM classifier is employed for classification purpose. Haralick texture features based glaucoma detection using digital fundus image is presented in [4]. Thirteen Haralick features are extracted using the computed GLCM. Finally, these extracted features are fed to the K-Nearest Neighbour classifier.

To detect glaucoma using moment and wavelet features to prevent vision loss is discussed in [5]. Three wavelets; Daubechies, symlets and Bi-orthogonal are used to extract features. Fifteen moment features are also computed from the combination of sub-bands. The extracted features are applied to classifier such as SVM and KNN for classification. An approach for detection of glaucoma using GLCM feature and logistic regression classifier from ocular thermal images is discussed in [6]. Using linear transformation, the images are transformed from RGB to YIQ image. Four features are extracted in GLCM technique such as Energy, Homogeneity, contrast, and correlation. Then they are used to train a logistic regression classifier for diagnose glaucoma.

The detection of glaucoma using different classifiers is implemented in [7]. Discrete wavelet transform is used to extract energy features obtained from the three filters: Daubechies, symlets and Biorthogonal. The detection and classification is done using

random forest, SVM, and naïve Bayes. An analysis of optic cup feature in colour fundus image using stochastic watershed transformation for glaucoma diagnosis is explained in [8]. Anatomical characteristics are used for the classification.

The features of wavelet energy based glaucoma detection using neural network is discussed in [9]. Energy distribution is used to find the texture features. Then, the extracted features are fed to back propagation and multilayer perceptron neural network for classification in view of normal extracted features. An automatic detection of glaucoma using SVM classifier from digital fundus images is described in [10]. First step is the pre-processing techniques such as contrast enhancement, noise removal and second is the feature extraction which uses principal component analysis method. Finally SVM method is used for image classification.

In this paper, GLCM based texture features for the diagnosis of glaucoma is presented. The rest of the paper is organized as follows: Section 2 describes the methods and materials for the proposed system. The analysis of the system is discussed in section 3 and conclusion is made in the last section.

2. Methods and Materials

In this section, an efficient glaucomatous image classification system is proposed using GLCM with optical density transformation approaches. In addition, binary SVM classifier is employed for automated fundus image classification into either normal or abnormal (glaucomatous) image. The success of any pattern recognition system relies on the appropriate design of two computational modules: feature extraction and classification. These two modules are discussed in detail. Figure 1 shows the design of the proposed system.

In any machine learning and pattern recognition approaches, feature extraction is considered as a critical process because the features obtained from this process directly influence the efficacy of the classification process. Also, it is defined as the first stage of intelligent image analysis, which tends to remove the redundant data and possess more intrinsic content of the original data. Thus, the task of feature extraction emphasizes the significant image information.

The proposed features are extracted for ROI only. ROI is selected using intensity value of pixels, whereas an approximate region of size 360x360 pixels is cropped automatically around the identified brightest intensity pixels. Commonly, the optic disc

has bright characteristics features and high contrast in the Green channel of the retinal fundus image. As green channel provides better contrast than the other two planes, it is only taken into account for ROI identification and the proposed features are extracted for the same.

GLCM is the basis for texture features [11]. This matrix is square with dimension N_g , where N_g is the number of gray levels in the image. Element $[i,j]$ of the matrix is generated by counting the number of times a pixel with value i is adjacent to a pixel with value j and then dividing the entire matrix by the total number of such comparisons made. Each entry is therefore considered to be the probability that a pixel with value i will be found adjacent to a pixel of value j .

$$G = \begin{matrix} & p_{1,1} & p_{1,2} & \dots & p_{1,N_g} \\ p_{2,1} & p_{2,2} & \dots & p_{2,N_g} \\ \vdots & \vdots & \dots & \vdots \\ p_{N_g,1} & p_{N_g,2} & \dots & p_{N_g,N_g} \end{matrix} \quad (1)$$

The GLCM is normalized so that the sum of its elements is equal to 1. Each element i, j in the normalized GLCM is the joint probability occurrence of pixel pairs with a defined spatial relationship having gray level values i and j in the image.

Let us consider p is the normalized GLCM of the input texture image. Contrast is a measure of the intensity contrast between a pixel and its neighbor over the whole image and given by the equation (2) and the measure of how correlated a pixel is to its neighbor over the whole image is given by the equation (3).

$$\text{Contrast} = \sum_{i,j} |i - j|^2 p(i, j)^2 \quad (2)$$

$$\text{Correlation} = \sum_{i,j} \frac{(i - \mu_i)(j - \mu_j) p(i, j)}{\sigma_i \sigma_j} \quad (3)$$

The energy is the sum squared element in the normalized GLCM and given by the equation (4) and the homogeneity in equation (5) is a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$Energy = \sum_{i,j} p(i,j)^2$$

$$Homogeneity = \sum_{i,j} \frac{p(i,j)}{1 + |i - j|} \quad (5)$$

Initially, these 4 features are extracted for the ROI obtained from the original image. Then the ROI is transformed into optical density image which is defined by

$$OD_{ij} = \log \left(\frac{I_{ij}}{I_o} \right) \quad (6)$$

where I_o is the average intensity and I_{ij} is the intensity at each pixel. From the OD image, GLCM features are computed using equation (2-6) as well and all are combined to form the feature database.

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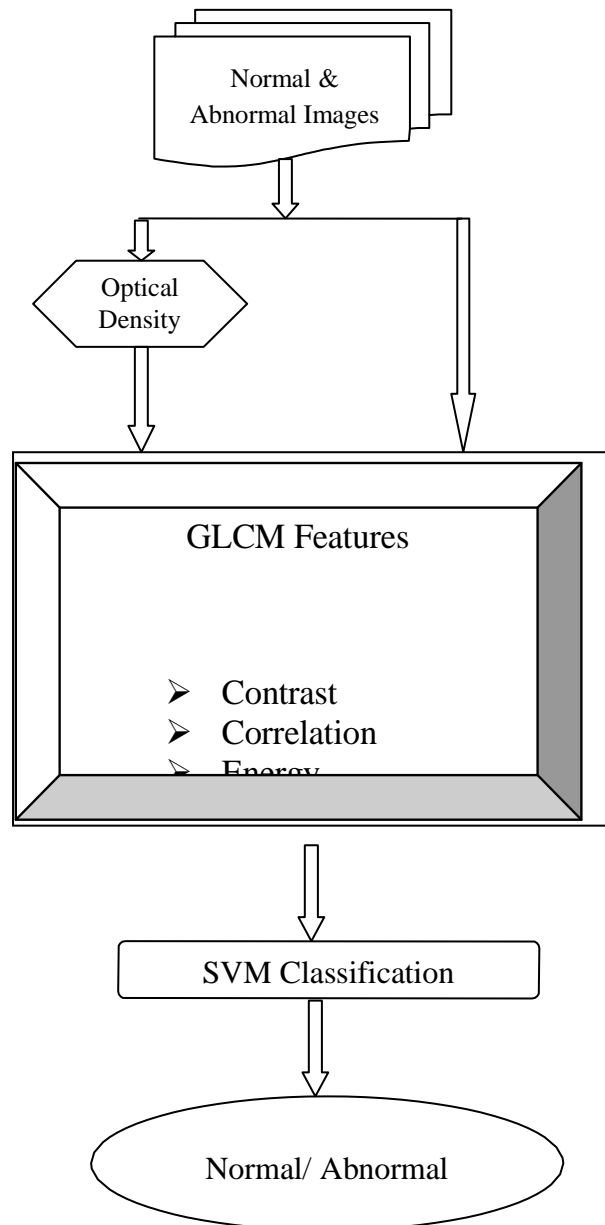


Figure 1 Glaucomatous image classification system using GLCM and optical density transformation

Hence the dimension of the texture features is 8 for a corresponding fundus image. This process is repeated for all training fundus images. Then a binary SVM classifier is trained using the above features. To test an unknown fundus image, the same complex texture features are extracted and given to the trained SVM classifier which gives the classification output based on the support vectors.

3. Analysis of the System

In total, 200 fundus images of resolution 1504 x 1000 pixels are used to analyze the proposed GLCM based glaucomatous image classification system. The number of images in each category i.e., normal and abnormal is 100. Figure 2 shows the sample normal and abnormal fundus image. Among the 100 images in each category, 50% of images are randomly selected for training SVM classifier and the remaining fundus images are tested by the trained classifier. This process is repeated for 10 times using different samples. Figure 3 shows the obtained confusion matrix for GLCM features.



(a)

(b)

Figure 3 Fundus image (a) Normal case (b) Glaucoma Patient



Figure 3 Confusion matrix of the proposed glaucomatous image classification system

(a) GLCM features alone (b) GLCM + OD features

It is inferred from Figure 2 that five (5) abnormal images are misclassified as normal and among 50 normal images eight (8) images are misclassified while using the GLCM features. However, this misclassification is reduced by using the OD features along with GLCM features. Only 2 abnormal images are misclassified by combining OD features with GLCM features. The ROC plot of the proposed glaucomatous image classification system using GLCM features is shown in Figure 3. The maximum Az value achieved by the proposed classification system is 0.95 while using GLCM with optical density features.

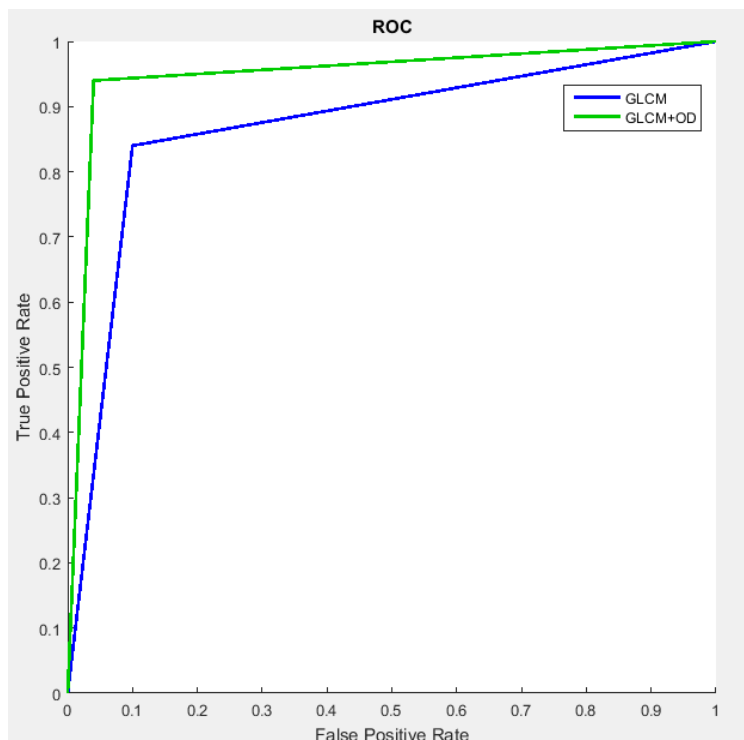


Figure 4 ROC plot of the proposed classification system using GLCM features

In this section, an efficient glaucomatous image classification system is proposed using GLCM with optical density transformation approaches. In addition, binary SVM classifier is employed for automated fundus image classification into either normal or abnormal (glaucomatous) image. The success of any pattern recognition system relies on the appropriate design of two computational modules: feature extraction and classification. These two modules are discussed in detail. Figure 1 shows the design of the proposed system. Also, it is defined as the first stage of intelligent image analysis, which tends to remove the redundant data and possess more intrinsic content of the original data. Thus, the task of feature extraction emphasizes the significant image information.

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4. Conclusion

In this paper, an efficient approach for the diagnosis of glaucoma is presented using GLCM and SVM classifier. It uses GLCM features efficiently by the concept of optical density transformation. For classification, SVM classifier which automatically classifies the given image into normal or abnormal is used. GLCM features obtained from the original image gives 87% accuracy while the GLCM features by optical density image along with the original image provides 95% accuracy. It uses GLCM features efficiently by the concept of optical density transformation. For classification, SVM classifier which automatically classifies the given image into normal or abnormal is used. The proposed approach is an non-invasive approach and it gives an second opinion to the ophthalmologists to make their decision efficiently.

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