MULTIWAVELET TRANSFORM BASED GLAUCOMA CLASSIFICATION USING RANDOM FOREST

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Abstract:

Glaucoma is a group of eye disorders that damage the optic nerve, essential for good vision. Often this damage comes from an abnormally high pressure in the eye. The early diagnosis of glaucoma detection is required because it leads to loss of vision. The fundus images are decomposed by Multi Wavelet Transform (MWT). Then the sub-band coefficients of MWT are extracted by using energy features. Then the redundant features are reduced by Principal Component Analysis (PCA). Finally, Random Forest (RF) classifier is used for prediction. The classification results are obtained in the experimental results and discussion section. The system produces classification accuracy of 93% by using MWT based PCA reduction and RF classifier.

Keywords: Glaucoma Classification, Multi-wavelet Transform, Principal Component Analysis, Random Forest Classifier

1. Introduction

SVM based glaucoma diagnosis is discussed in [1]. The input fundus image is extracted initially to separate the region of interest. Then the optic cup region is detected. The optical cup and binary smoothing is found. Cup is eventually detected at a disc ratio. Retinal images identified automatic glaucoma detection in [2]. [3]. For the position of the disc, the distance transformation is used. PCA is then used to diagnose glaucoma.

Focal edge correlation for treatment of glaucoma is discussed in [3]. Edges of corner structures associated. The highest arch from the Hough circular transformation is first done in order to locate the focal borders. Glaucoma automated treatment of Haralick texture characteristics is discussed in [4]. Initially, the preprocessing is made by gray level co-occurrence matrix and haralick features. Finally, classification is made by k-nearest neighbour.

Haralick texture features Glaucoma controlled treatment is des cribbed in [5-6]. The fundus images are extracted by texture features. The statistical analysis and PCA method are used for feature extraction. Classification is made by neural network architecture.Using texture features extraction detection of glaucoma is described in [7]. The red channel is extracted and contrast adjustment is made in pre-processing stage. By means of strong transformation, morphologie, and k-means clustering, the field of interest is derived. The characteristics are derived by a random field approximation and a co-occurrence matrix at a grey level. Finally, the SVM classificator forecasts.

Gray level co-occurrence matrix-based characteristics The fundus image classification is defined in [8]. The analytical wavelet transform was originally used to derive features and the classification is used by the SVM classifier.

In this paper, MWT-PCA-RF system is presented for the classification of fundus image based glaucoma diagnosis. The remaining paper is as follows: Section 2 addresses the automatic and practical aspects of the MWT-PCA-RF System. Section 3 explains the performance of the MWT-PCA-RF. Finally, there is a discussion of the capacity of MWT-PCA-RF.

2. Methods and Materials

A wavelet can be decomposed in a variety of forms to explore n-dimensional data in multi-resolution. Here we'll look at the three methods in PyWavelets currently in place. 2D cases are seen, but each solution is straightforward for the n-dimensional case. The most common method for the multi-level discreet wavelet transformation requires further decomposition at each subsequent level of the approximation subband. The Mallat decomposition is often also named. 2D generates four distinct sets of coefficients in the discrete wavelet transform, which correspond to the four potential variations across the two independent axes for wavelet decomposition. (There are 2**n coefficient sets in n-dimensions). Only the approximation coefficients (the subband of low pass) are further decomposed for future levels of decomposition.

The main aim of this study is to investigate MWT for glaucoma diagnosis using fundus images. The great possibilities offered by medical imaging modalities are allowed to achieve the goal of this study. Figure 1 shows the MWT-PCA-RF system for glaucoma diagnosis.

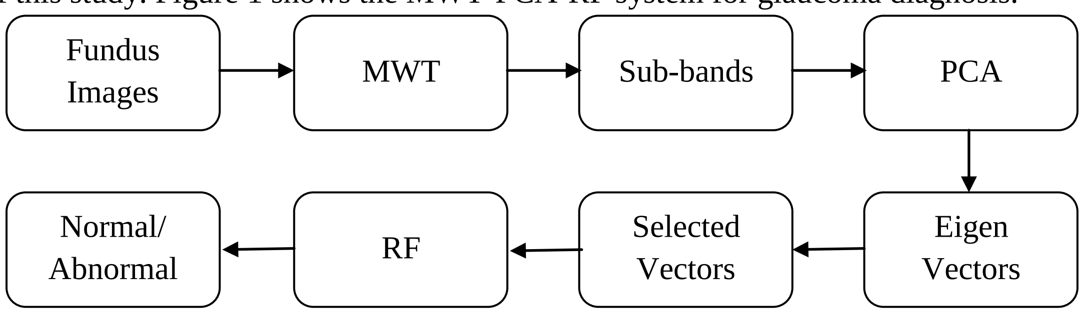

Figure 1 MWT-PCA-RF system for glaucoma diagnosis.

The MWT-PCA-RF system utilizes the sub-bands coefficients of MWT in a statistical manner by using PCA. First, the sub-band coefficients are computed from the decomposition of fundus images by MWT. Then the computed sub-band coefficients are transformed into PCA subspace. MWT is an advancement of wavelet theory. The main difference between MWT and conventional wavelets is the number of scaling and mother wavelets used to represent the image of signal. The conventional wavelets use a single scaling and mother wavelets whereas MWT uses more than one of both functions. MWT is defined by

$$\Psi = \left(\Psi_1, \Psi_2, \Psi_3, \ldots.. \Psi_n,\right)^T \tag{1}$$

where n is the number of mother wavelets and T is the transpose. Similarly the scaling function is defined by

$$\Phi = \left(\Phi_1, \Phi_2, \Phi_3, \ldots.. \Phi_n,\right)^T \tag{1}$$

Using the defined scaling and mother wavelets, MWT decomposition is employed on fundus images. After decomposition, PCA is applied on the obtained sub-bands. It is simple and extracts relevant information from databases which are very difficult to distinguish. It reduces the computational complexity of many real time applications. More information can be found in [9].

A recent machine learning algorithm named RF is used for classification [10]. It can be used for regression analysis also. It has a tree structure with many classifiers called as node. It constructs number of decision tress which is equal to the number of classifiers. Before training, the extracted PCA features from MWT sub-band coefficients are projected to another sub-space which is generated randomly.

3. Results and Discussion

The ability of the MWT-PCA-RF system to distinguish between healthy and glaucoma patients is investigated. Moreover, the significant Eigen vectors in distinguishing the healthy from glaucoma fundus images are identified. This is performed by the application of MWT-PCA-RF system for different number of Eigen vectors. The performance of MWT-PCA-RF system is validated on 100 fundus images obtained from [10-13]. Figure 2 shows sample fundus images.

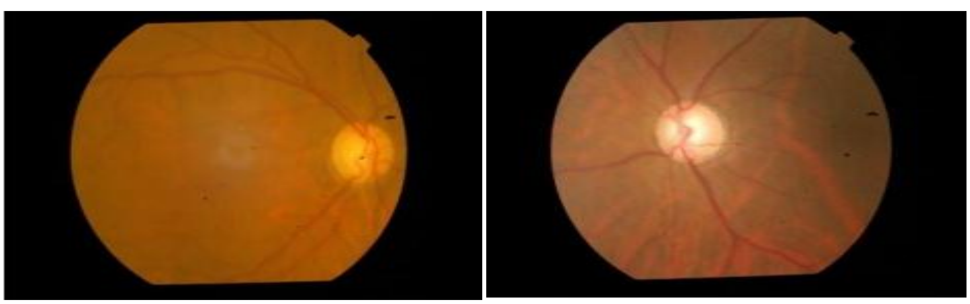

Figure 2 Sample fundus images; normal (left image) and abnormal (right image)

The distribution of the significant number of Eigen vectors that lead to best accuracy of MWT-PCA-RF system is given in Table 1.Also Tables 2 to 3 shows the sensitivity and specificity of MWT-PCA-RF system.

Table 1 Accuracy of MWT-PCA-RF system for different distribution Eigen vectors and MWT levels

MWT Level	Distribution of Eigen Vectors in Ascending order				
	10	20	30	40	50

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1	65.00	70.00	80.00	75.00	68.00
2	69.00	74.00	86.00	81.00	74.00
3	73.00	78.00	93.00	86.00	79.00
4	67.00	72.00	82.00	77.00	70.00

Table 2 Sensitivity of MWT-PCA-RF system for different distribution Eigen vectors and MWT levels

MWT Level	Distribution of Eigen Vectors in Ascending order				
	10	20	30	40	50
1	60.00	66.00	76.00	72.00	66.00
2	64.00	70.00	84.00	80.00	74.00
3	70.00	76.00	94.00	90.00	84.00
4	62.00	68.00	78.00	74.00	68.00

Table 3 Specificity of MWT-PCA-RF system for different distribution Eigen vectors and MWT levels

MWT Level	Distribution of Eigen Vectors in Ascending order				
	10	20	30	40	50
1	70.00	74.00	84.00	78.00	70.00
2	74.00	78.00	88.00	82.00	74.00
3	76.00	80.00	92.00	86.00	78.00
4	72.00	76.00	86.00	80.00	72.00

From the above performance tables, it is evident that 30% of Eigen vectors from the PCA of MWT sub-band coefficients gives maximum accuracy of 93% for glaucoma diagnosis. Also it is noted that 94% and 92% of sensitivity and specificity are obtained by the same set of Eigen vectors. Figure 2 shows the best performance of MWT-PCA-RF system

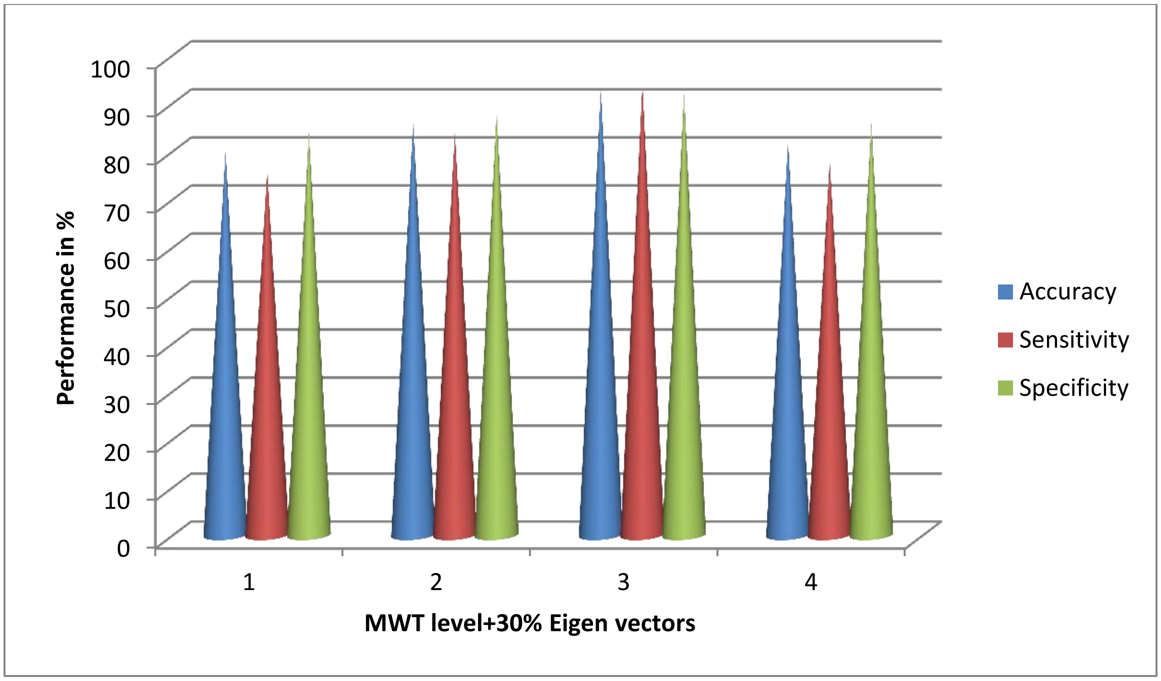

Figure 3 Best performance of MWT-PCA-RF system for glaucoma diagnosis.

4. Conclusion

In this study, MWT-PCA-RF system is presented for the classification of fundus image based glaucoma diagnosis. Early diagnosis is crucial as the glaucoma develops vision loss gradually. The importance of the selected PCA features of MWT coefficients at different levels are determined by RF. The evaluation of MWT-PCA-RF system demonstrated in results and discussion section shows the potential of MWT-PCA features for glaucoma diagnosis using fundus images. Experiments shows that 30% biggest Eigen vectors extracted by PCA at 3rd level MWT gives promising results than other levels and distribution Eigen vectors. The system provides maximum accuracy of 93% with capable sensitivity and specificity.

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