Detection of glaucoma using two dimensional tensor empirical wavelet transform

Shruti Jain¹ · Ayodeji Olalekan Salau²

© Springer Nature Switzerland AG 2019

Abstract

Retinal image analysis is extensively used in the medical field for the detection of abnormalities in the eye. Amongst the several abnormalities in the eye, glaucoma has been identified as the second major cause of blindness. The glaucoma disease are of various types, out of which close angle glaucoma causes more pain and has the most effect on eye vision in comparison with the open angle glaucoma. In this paper, a futuristic computer aided classification method is designed and differentiated in terms of its sensitivity, specificity, and classification accuracy. The proposed method is used to detect glaucoma eye fundus from normal eye images using tensor based empirical wavelet transform (tensor based EWT). The method was tested on samples obtained from the online database; Medical image group Analysis, and an accuracy of 98.7% detection rate was achieved. The tensor based EWT yields 22% improvement in comparison with the littlewood EWT. The performance of the Tensor based EWT technique was compared with existing techniques and was found to outperform existing results.

Keywords Glaucoma · Empirical wavelet transform · Correntropy features · Support vector machine

1 Introduction

Retinal image analysis is a procedure which examines the computational analysis to assess the eye. The aim of using this analysis is to minimize the variability that occurs between clinicians, following the progressive and systematic characteristics of the eye. Glaucoma is a disease in which eye vision is lost due to the damage of the optic nerves. Early detection of glaucoma is important as recovering damaged optic nerves is a very difficult task. Glaucoma causes the fluid pressure in the eye to increase and causes harm to the optic nerve leading to vision loss [1]. Around 60 million people about the ages of 40 suffer from glaucoma [2]. This disease can be characterized into various types, namely: normal tension glaucoma, open-angle glaucoma, closed angle glaucoma pigmentary glaucoma, exfoliation syndrome, and trauma-related

glaucoma. The angle signifies the distance between the cornea and the iris. If the distance is small then it is referred to as close angle glaucoma, while if the angle is large then it is called open-angle glaucoma. People suffering from open-angle glaucoma have mostly been observed to have cardiovascular diseases or high rate of mortality. Women are more susceptible to closed angle glaucoma. Indicative from 2010 statistics, 4.47 million people around the world suffer from open-angle glaucoma; this is predicted to increase to 58.6 million in 2020 [2]. Approximately, about 11.2 million people suffer from glaucoma with ages above 40 [3]. Therefore, various methods for the early detection of glaucoma which are based on features like diabetics, age (above 60), increase in IOP, eye injuries, family history of glaucoma, low blood pressure, migraines, and reduction in the thickness of the cornea have been used in the past.

✉ Ayodeji Olalekan Salau, ayodejisalau98@gmail.com; Shruti Jain, shruti.jain@juit.ac.in | ¹Department of ECE, Jaypee University of Information Technology, Solan, Himachal Pradesh, India. ²Department of Electrical/Electronics and Computer Engineering, Afe Babalola University, Ado-Ekiti, Nigeria.

An adaptive threshold technique was proposed in [4] to identify glaucoma via segmentation of optic disk (OD) and optic cup giving a 90% accuracy while cup to disc ratio (CDR) based method was proposed in [5] for the detection of glaucoma giving an accuracy of 98.12%. In [6], an optic disc segmentation approach was proposed which used circular Hough transform and curve fitting from fundus images to give a detection accuracy of 68%. Optic disc and cup segmentation using k-mean clustering was implemented in [7]. Texture feature and higher order spectra based algorithm was developed for the detection of glaucoma and for the classification of retinal images in [8]. An accuracy of 91% was achieved using random forest classifier. Dua et al. [9] extracted texture features such as energy signatures using 2D DWT for the detection of glaucoma which gave an accuracy of 93% using support vector machine (SVM) and naïve Bayes classifier with ten-fold validation. Patil et al. [10] proposed a method which used super pixel classification for CDR to diagnose glaucoma. Color contrast improvement and image filtration techniques were used for preprocessing. Dey et al. [11] examined automated glaucoma selection by enhancing contrast and noise removal using PCA-SVM which gave an accuracy of 96%. In [12], an accuracy of 97% was achieved for the detection of glaucoma using SVM classifier and in [13], a detection accuracy of 86% was achieved using standard pattern recognition pipeline with SVM.

In this paper, a futuristic computer aided classification (CAC) method for the classification of glaucoma is proposed using Tensor-based EWT. Green, blue, gray, and red 2D channels were extracted from three-dimensional fundus images. EWT components and frequency spectra were analyzed using Tensor technique. The correntropy features of the decomposed images were calculated. Using t test algorithm best features were selected and on the basis of the selected features, images were classified with ten-fold cross-validation SVM.

The rest of this paper is divided into the following sections. Section 2 describes the materials and

proposed methodology. Section 3 explains the results and discusses the proposed method for the detection of glaucoma which is followed by a conclusion and future work in Sect. 4.

2 Materials and methodology

In this section, we propose a method for the detection/diagnosis of normal and glaucoma images using two-dimensional Tensor EWT. The proposed methodology is shown in Fig. 1.

For the retinal image analysis, retinal fundus images, optical coherence tomography (OCT), or multifocal electroretinogram (mfERG) images are used. Fundus images are used for the diagnosis of glaucoma and diabetic retinopathy. To analyze the structural and functional abnormalities of the eye, OCT and mfERG were used. These approaches were used to observe the variability and quantify the progression of the disease. Medical Image Analysis Group online database was used as the image database for which our method was tested on. This database consists of 250 fundus images of glaucoma and 255 images of eyes of healthy people. The images are available in 24-bit jpeg with different resolutions. From the three dimensional (3D) red green blue images, two dimensional (2D) red green blue channels were extracted in the pre-processing stage. Figure 2a represents the extracted channels from the glaucoma images, and Fig. 2b represents the extracted channels from normal images. Correntropy features are extracted using 2D Tensor EWT which were selected using the t test.

EWT can be used as a 1D or 2D detection technique [14, 15]. In 1D EWT, rows and columns are independent of each other; this occurrence results in a different set of filters for the different Fourier boundaries [16–18]. It also causes discontinuity in the filter bank because different information are available on the same scale for each row and column. To overcome this challenge, the Tensor approach is proposed in which one filter bank is designed

Fig. 1 Proposed methodology

Fig. 2 2D channels of **a** glaucoma images, and **b** normal images

for a row while another is designed for all columns as shown in Fig. 3. In the filter, decomposed images were obtained from where Correntropy features were extracted.

Correntropy features $V(A, B)$ are calculated using Eq. (1)

$$V(A, B) = E[k(A, B)] = \int k(a, b) dF_{AB}(a, b) \quad (1)$$

where $E[\cdot]$ denotes the mathematic expectation, $F_{AB}(a, b)$ denotes the joint distribution function of A and B , and $K(\cdot)$ denotes the shift variance kernel. The Gaussian kernel is used for simulations. If A and B are unknown, then the Correntropy estimator $\widehat{V}_N(A, B)$ is defined by Eq. (2).

$$\widehat{V}_N(A, B) = \frac{1}{N} \sum_{i=1}^N k_\sigma(a_i, b_i) = \frac{1}{N\sigma\sqrt{2\pi}} \sum_{i=1}^N \exp\left[-\frac{(a_i - b_i)^2}{2\sigma^2}\right] \quad (2)$$

EWT is a recently proposed procedure used to adaptively identify the different modes of signals generated from the processing of images. This technique builds the empirical wavelets used to characterize the signal by using different detected modes [19]. The frequency spectrum of the processed signal is detected on the basis of which modes are constructed. Modes are referred to as the major components of a signal which characterize the signal fully. Features which are extracted from the decomposed images are called Correntropy. The main purpose of the EWT method is signal decomposition. EWT works basically on the principle of Fourier spectrum signal decomposition which depends on the analyzed signal.

EWT consists of two main steps:

- Detection of the Fourier boundaries. It builds the corresponding wavelet based on these boundaries.
- Filtering the image from the obtained filter bank to get its components.

In EWT, the Fourier spectrum range from 0 to π is divided into M number of parts. These M number of parts are called segments. The limit of each segment is given by ω_m , ranging from $\omega_0 = 0$ to $\omega_m = \pi$. In the transition phase, T_m depends upon ω_m which has a width of $2\epsilon_m$, where $\epsilon_m = a\omega_m$ for $0 < a < 1$. Empirical wavelets are defined by each neighboring section for the constructed filter bank. The empirical scaling function $\xi_m(X)$ and the empirical wavelets $\varsigma_m(X)$ are given by Eqs. (3) and (4) [20], respectively.

$$\xi_m(X) = \begin{cases} 1 & \text{if } |X| \leq (1-a)\omega_m \\ \cos\left[\frac{\pi}{2}Y(a-\omega_m)\right] & \text{if } (1-a)\omega_m \leq |X| \leq (1+a)\omega_m \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

$$\varsigma_m(X) = \begin{cases} 1 & \text{if } (1+a)\omega_m \leq |X| \leq (1-a)\omega_{m+1} \\ \cos\left[\frac{\pi}{2}Y(a, \omega_{m+1})\right] & \text{if } (1-a)\omega_{m+1} \leq |X| \leq (1+a)\omega_{m+1} \\ \sin\left[\frac{\pi}{2}Y(a, \omega_m)\right] & \text{if } (1-a)\omega_m \leq |X| \leq (1+a)\omega_m \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

where $Y(a, \omega_m)$ and $Y(a, \omega_{m+1})$ are defined by Eqs. (5) and (6), respectively.

$$Y(a, \omega_m) = F\left(\frac{1}{2a\omega_m}(|X| - (1-a)\omega_m)\right) \quad (5)$$

Fig. 3 Proposed tensor EWT

$$Y(a, \omega_{m+1}) = F\left(\frac{1}{2a\omega_{m+1}}(|X| - (1-a)\omega_{m+1})\right) \quad (6)$$

Figures 4 and 5 represent the sub-band images using Tensor EWT. Lastly, SVM classifier is used to distinguish between glaucoma and normal images. Different classifiers are used in literature for fundus image classification, but in this paper, authors have used support vector machine (SVM) classifier to perform the classification task. SVM is a supervised discrimination method that creates a hyperplane using labelled data and then classifies the testing data. SVM classification relies on selection of kernels. Authors have used linear kernel as it provides desirable results in terms of detection accuracy for classification of fundus images. Equation (7) explains the linear kernels.

$$K(\alpha, \alpha_i) = \sum \vec{w} \cdot \overline{\alpha, \alpha_i} + \beta \quad (7)$$

where α is the input vector, α_i is the support vector, β is the bias, and w is the weight vector.

Fig. 4 2D EWT tensor components of the glaucoma image

Fig. 5 2D EWT tensor components of the normal image

3 Results and discussion

Fast Fourier transform (FFT), Gabor wavelet transform, Fourier power spectrum, discrete wavelet transform, and empirical wavelet transform (EWT) are some different types of transform domain methods that are used for feature extraction. EWT yields better results among various wavelet methods as it does not use any predefined function. This section presents the procedure employed for the detection of glaucoma based on Tensor EWT and correntropy features. These features are acquired from the EWT decomposed images as EWT decomposes the image into several frequency bands based on the information present in the image. In EWT, the basis function is generated based on the information obtained from the signal or image. Tensor, littlewood, curvelet, and ridgelet are some of the various EWT techniques. EWT identifies the different modes of the signal which help in forming frequency spectra which are used to build the empirical wavelets as shown in Fig. 6. Correntropy features are evaluated from the EWT components, and are further normalized and ranked on the basis of student's t test criteria. Although there are many other optimization techniques such as particle swarm optimization [21], genetic algorithm [22], cuckoo search [23] etc.; statistical analysis is also one of the feature selection techniques. Similarly, t test and ANOVA are also frequently used statistical tools. t test is employed in this work to provide the inferential and parametric significance of the extracted features by analyzing the variation in the means of the normal and abnormal classes. It is frequently used for a normally

distributed set of continuous data. The statistical significance of the t test is given by the significance value (p value) of the test which should be less than 0.05 to state if any feature is significant enough to reject the null hypothesis.

Figures 4 and 5 present the coefficients obtained from the 2D tensor EWT components of the gray, red, blue, and green channel of the glaucoma and normal affected fundus eye images, respectively. It was observed that the efficiency of detection is at variance with respect to the horizontal and vertical directions. Practically, these transforms provide sparse representations of images which can be used for restoration purposes (denoising, deblurring).

In Tables 1, 2, 3, and 4, we present the best six t -values of each green, gray, red, and blue channel features which are used for further classification. These tables provide values of correntropy in columns noted as normal and glaucoma which are positive and negative values, respectively. A positive value indicates the normal, while negative indicates a glaucoma affected image. As experiments were performed for every image, different correntropy values were obtained. In Tables 1, 2, 3, and 4, it was mentioned that CE_3 signifies 3rd component of 1st image. All the values presented in Tables 1, 2, 3, and 4 were considered for the perfect classification of normal and glaucoma cases.

For normal data, the values are positive while for glaucoma data the values are negative. For the purpose of experimentation, we have used 250 fundus images of glaucoma and 255 images of eyes of healthy people. Due to the constraint of space and the numerous results achieved, authors have reported only 6 values of each

Fig. 6 Frequency spectrum using tensor EWT **a** glaucoma image, and **b** normal image

Table 1 Best six *t*-values for the gray channel

Correntropy values	Normal	Glaucoma	<i>t</i> -values
CE_{33}	1.08	− 3.40	4.03
CE_{31}	0.09	− 0.90	5.15
CE_{12}	1.34	− 1.34	5.17
CE_{45}	0.25	− 4.17	6.17
CE_{26}	1.51	− 2.52	7.26
CE_{61}	1.65	− 4.34	7.59

CE_{31} signifies the 3rd component of the 1st image and is likewise for all other correntropy values

Table 2 Best six *t*-values for the green channel

Correntropy Values	Normal	Glaucoma	<i>t</i> -values
CE_{66}	1.43	− 0.97	0.51
CE_{64}	1.64	− 1.11	1.94
CE_{34}	1.16	− 1.39	2.78
CE_{25}	0.58	− 1.84	3.91
CE_{16}	0.81	− 1.51	4.03
CE_{11}	0.99	− 1.11	4.45

CE_{64} signifies the 6th component of the 4th image and is likewise for all other correntropy values

Table 3 Best six *t*-values for the red channel

Correntropy values	Normal	Glaucoma	<i>t</i> -value
CE_{15}	1.51	− 0.12	2.79
CE_{22}	0.91	− 0.86	2.94
CE_{31}	0.39	− 1.02	3.27
CE_{52}	0.79	− 0.37	4.08
CE_{23}	1.10	− 0.39	5.11
CE_{35}	0.44	− 1.44	5.25

Table 4 Best six *t*-values for the blue channel

Correntropy values	Normal	Glaucoma	<i>t</i> -value
CE_{34}	1.59	− 1.54	1.81
CE_{25}	0.46	− 3.54	2.88
CE_{63}	0.30	− 1.44	3.91
CE_{21}	1.20	− 3.05	6.05
CE_{26}	1.03	− 2.71	6.56
CE_{16}	1.46	− 0.67	7.08

Table 5 Observation table of littlewood and tensor EWT

S/ No.	Types of EWT	Accuracy (%)	Sensitivity (%)	Specificity (%)
1.	Tensor EWT	98.7	90	98.75
2.	Littlewood EWT	76.5	82.69	54.54

channel based on the highest values of the *t* test. The best results were obtained from the green channel for CE_{11} as presented in Table 2.

After feature selection, images are classified using SVM classifier as utilized by [24]. Ten cross validation approaches were used to detect glaucoma at the early stage. The procedure of gathering the test data into its related class is known as arrangement of dataset. Arrangement is sorted as regulated and unsupervised characterization. The SVM classifier goes under the class of regulated machine learning and is seen to under perform at the premise of number-crunching ideas and factual hypothesis [25, 26]. SVM classifier can characterize both straight and non-direct order data. Confusion matrix is a term given to a set of values written in the form of a matrix which is an indication of the performance of the classification model on a set of values (test data) for which the exact values are known.

Table 5 shows the obtained accuracy, specificity, and sensitivity using Tensor EWT and Littlewood EWT. These metrics describe the efficiency of the classification method.

True positive (TP) is the glaucoma predicted in the presence of the Normal image of the dataset (Eyes of healthy people).

True negative (TN) is the Normal data predicted in the absence of glaucoma.

False positive (FP) is the prediction of glaucoma in the absence of normal data.

False negative (FN) is the prediction of normal data in the absence of glaucoma.

The performance metric used for the evaluation of the proposed method are: sensitivity (Sens), specificity (Spec), and accuracy (Acc). Sensitivity represents the probability of predicting the actual class of glaucoma as expressed in Eq. (8). Specificity represents the prediction of the Normal class as expressed in Eq. (9). Accuracy is the amount of correct predictions made compared with the total number of predictions made as expressed in Eq. (10).

$$\text{Sens} = \frac{TP}{TP + FN} \quad (8)$$

Table 6 Comparison of different proposed methods for the detection of glaucoma

Authors	Proposed methods	Features extracted	Classifier	Accuracy (%)
Implemented work	Detection using texture features	Tensor EWT + correntropy	SVM	98.7
Bock et al. [13]	Texture analysis for detection	Pixel intensity values, FFT coefficients	SVM	86
Dua et al. [9]	Detection using texture features	Energy signatures	SVM	93.33
Dey et al. [11]	NA	NA	SVM	96
Singh et al. [12]	Detection of glaucoma	Red, green and blue values	SVM	97

$$Spec = \frac{TN}{TN + FP} \quad (9)$$

$$Acc = \frac{TP + TN}{FP + TP + FN + TN} \quad (10)$$

In the existing littlewood algorithm, Pseudo polar FFT is first calculated then filter banks are made with the help of Fourier boundaries. Lastly, extracted channels are passed through the designed filter bank to obtain subband images. While, in our proposed technique, all the work is carried out using the row and column vectors individually. This gives better results in comparison with the littlewood technique. As a result of this, the calculated accuracy using Tensor EWT is 98.7% while that of littlewood is 76.5% giving a 22% improvement. Comparison with other state of the art techniques for the detection of normal and glaucoma images is presented in Table 6.

4 Conclusion

Glaucoma is an optic nerve disease that leads to blindness if not treated early. Nowadays, glaucoma detection is an important research topic in the field of medicine. Different techniques have been proposed in the past for the detection of glaucoma but these techniques are quite expensive and are not so efficient in terms of detection accuracy. The main aim of this research paper is to detect normal and glaucoma based images using 2D Tensor EWT. EWT components and their frequency spectra were evaluated for all the 2D channels. Correntropy features were calculated, followed by the use of the *t* test algorithm to get the best features. Ten cross validation approaches were applied on the best features using SVM classifier for the classification of normal and glaucoma images. Lastly, the performance analysis of the 2D Tensor EWT and 2D Littlewood Paley EWT were compared with different performance evaluation parameters. The percentage improvement in the accuracy of the tensor based EWT technique is higher than that of the 2D Littlewood Paley EWT by 22%. It is the view of the authors, that the method presented in this paper is also useful for the detection of Diabetics

Retinopathy, Fatty Liver detection, and early stages of Ovarian Cancer.

Compliance with ethical standards

Conflict of interest The authors declare that there is no conflict of interest of any sort for this research.

References

1. <https://www.glaucoma.org/glaucoma/types-of-glaucoma.php>. Accessed 20 July 2019
2. GBD 2015 Mortality and Causes of Death Collaborators (2015) Global, regional, and national life expectancy, all-cause mortality, and cause-specific mortality for 249 causes of death, 1980–2015: a systematic analysis for the Global Burden of Disease Study 2015. *388*(10053):1459–1544
3. George R, Ve RS, Vijaya L (2010) Glaucoma in India: estimated burden of disease. *J Glaucoma* 19(6):391–397
4. Agarwal A, Gulia S, Chaudhary S, Dutta MK, Burget R, Riha K (2015) Automatic glaucoma detection using adaptive threshold based technique in fundus image. In: 38th IEEE international conference on telecommunications and signal processing (TSP), pp 416–420
5. Pruthi J, Mukherjee S (2013) Computer based early diagnosis of glaucoma in biomedical data using image processing and automated early nerve fiber layer defects detection using feature extraction in retinal colored stereo fundus images. *Int J Sci Eng Res* 4(4):1822–1828
6. Gopalakrishnan A, Almazroa A, Raahemifar K, Lakshminarayanan V (2015) Optic disc segmentation using circular hough transform and curve fitting. In: 2nd international conference on opto-electronics and applied optics (IEM OPTRONIX). <https://doi.org/10.1109/optronix.2015.7345530>
7. Ayub J, Ahmad J, Muhammad J (2016) Glaucoma detection through optic disc and cup segmentation using k-mean clustering. In: International conference on computing, electronic and electrical engineering (ICE Cube). <https://doi.org/10.1109/icecube.2016.7495212>
8. Acharya UR, Dua S, Du X, Sree SV, Chua CK (2011) Automated diagnosis of glaucoma using texture and higher order spectra features. *IEEE Trans Inf Technol Biomed* 15(3):449–455
9. Dua S, Acharya UR, Chowriappa P, Sree SV (2012) Wavelet-based energy features for glaucomatous image classification. *IEEE Trans Inf Technol Biomed* 16(1):80–87
10. Patil HP, Kamkhedhar VS (2014) Analysis of human retinal images for automated glaucoma screening. *Int J Res Appl Sci Eng Technol: IJRASET* 2:371–377

11. Dey A, Bandyopadhyay SK (2016) Automated glaucoma detection using support vector machine classification method. *Br J Med Med Res: BJMMR* 11(12):1–12. <https://doi.org/10.9734/bjmmr/2016/19617>
12. Singh P, Marakarkandy B (2017) Comparative study of glaucoma detection using different classifiers. *Int J Electron Electr Comput Syst* 6(7):223–232
13. Bock R, Meier J, Nyl LG, Michelson G (2010) Glaucoma risk index: automated glaucoma detection from color fundus images. *Med Image Anal* 14:471–481
14. Shishir M, Ram Bilas P, Acharya R (2017) Automated diagnosis of glaucoma using empirical wavelet transform and correntropy features extracted from fundus images. *IEEE J Biomed Health Inform* 21(3):803–813
15. Gilles J (2013) Empirical wavelet transforms. *IEEE Trans Signal Process* 61(16):3999–4010
16. Thirumala K, Umarikar AC, Jain T (2015) Estimation of single-phase and three-phase power-quality indices using empirical wavelet transform. *IEEE Trans Power Deliv* 30(1):445–454
17. Liu W, Cao S, Chen Y (2016) Seismic time–frequency analysis via empirical wavelet transforms. *IEEE Geosci Remote Sens Lett* 13(1):28–32
18. Maheshwari S, Pachori RB, Acharya UR (2017) Automated diagnosis of glaucoma using empirical wavelet transform and correntropy features extracted from fundus images. *IEEE J Biomed Health Inform* 21(3):803–813
19. Kaushal S, Sharma SD, Jain S (2018) Investigation of image processing techniques for glaucoma detection in human eyes. In: 5th international conference on parallel, distributed and grid computing (PDGC), Jaypee University of Information technology, Waknaghat, Solan, HP, India, pp 747–753
20. Kaushal S, Sharma SD, Jain S (2018) Empirical wavelet transform based classification of glaucoma from retinal fundus images. *J Glob Trends Pharm Sci* 9(3):5887–5897
21. Raja C, Gangatharan N (2015) A hybrid swarm algorithm for optimizing glaucoma diagnosis. *Comput Biol Med* 63:196–207
22. Singh A, Dutta MK, Sarathi M, Uher V, Burget R (2016) Image processing based automatic diagnosis of glaucoma using wavelet features of segmented optic disc from fundus image. *Comput Methods Progr Biomed* 124(C):108–120
23. Liu X, Fu H (2014) PSO-based support vector machine with cuckoo search technique for clinical disease diagnoses. *Sci World J*. <https://doi.org/10.1155/2014/548483>
24. Jain S (2018) Classification of protein kinase B using discrete wavelet transform. *Int J Inf Technol* 10(2):211–216
25. Jain S, Sood M (2019) SVM Classification of cell survival/apoptotic death for color texture images of survival receptor proteins. *Int J Emerg Technol* 10(2):23–28
26. Jain S, Salau AO (2019) An image feature selection approach for dimensionality reduction based on kNN and SVM for Akt proteins. *Cogent Eng* 6(1):1–14. <https://doi.org/10.1080/23311916.2019.1599537>

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.