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Research Article

Dual Tree Complex Wavelet Transform Based Compression of Optical Coherence Tomography Images for Glaucoma Detection using Modular Neural Network

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Abstract: Background/Objectives: In worldwide, Glaucoma is basically a second major retinal disease that results in permanent blindness. Loss of Retinal Nerve Fiber Layer (RNFL) is the outcome of glaucoma disease. RNFL thickness is evaluated as a function of spatial information from Optical Coherence Tomography (OCT) images is a significant diagnostics indicator intended for glaucoma disease. However, due to factors such as low image contrast, speckle noise, high spatial resolution, exact compression of OCT is complex. To solve above issues, a Dual Tree Complex Wavelet Transform (DTCWT) based OCT image compression is proposed in this research work. Methods/Statistical analysis: The proposed method consists of five phases such as pre-processing, feature extraction, RNFL segmentation, glaucoma classification and OCT compression. Initially, OCT image is pre-processed for remove the speckle noise using kuan filter. Secondly, the RNFL based texture features are extracted by using Gray Level Covariance Matrix (GLCM) and the scrupulous features are chosen by Principal Component Analysis (PCA). Then, RNFL in OCT is segmented by Improved Artificial Bee Colony (IABC) clustering algorithm. After that the glaucoma is classified as normal, medium and severe by Modular Neural Network (MNN). Finally, DTCWT is used to compress the OCT image. Results: Experimental results show that the proposed MNN is efficient for detecting glaucoma compared with the existing detection algorithms.

Keywords: Classification, compression, feature extraction, Glaucoma, kuan filter, optical coherence tomography, RNFL, segmentation

INTRODUCTION

Glaucoma is among the most normal causes of everlasting blindness international with mean occurrence of 2.4% for all the ages and above 75 years ages of mean occurrence is 4.7% (Bock *et al*., 2010). Probably the most glaucoma symptoms depends to progressive atrophy of the Retinal Nerve Fiber Layer (RNFL) leading to scale back of the thickness of the layer. Degeneration of the nerve fibers begins several years prior to any changes within the sufferer's vision and prescient may also be registered. Unluckily, pathological changes within the RNFL could not get regenerated through present remedy. Only, an instantaneous therapy can help to stop development of the disorder. As a result, it is totally fascinating to have the disease detected as early as feasible. The RNFL thickness may also be measure by way of Optical Coherence Tomography (OCT), which is moderately new procedure with higher decision and deeper in penetration that indicates its diagnostic ability (Parikh *et al*., 2007). Time area OCT image is assessed in this research work for locating the thickness of RNFL. It's a 3D imaging method based on interferometry precept (Zhu *et al*., 2006). Despite the fact that OCT size of RNFL thickness provides the knowledge regarding the status of glaucoma (Mrugacz and Bakunowicz-Lazarczyk, 2005), the area of the OCT scan circle might organize the dimension of the RNFL thickness. Accordingly, right checking of OCT scans for the reason of measurement, reproducibility and longitudinal analysis is essential (Gabriele *et al*., 2008).

OCT is actually an imaging method at first evolved for providing the function and quantitative estimates with respect to the RNFL thickness. The OCT based RNFL measurements can be reproduced and had been depicted in the cross-sectional studies to be capable of discriminating the glaucomatous from healthful eyes (Schuman *et al*., 1996). Despite the fact that an earlier investigation instructed a possible role for the purpose of longitudinal OCT RNFL measurements for carrying out the monitoring of the glaucoma progression, the learning used a model version of the OCT tool that had a greater variability and scale back decision than the

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present commercially obtainable stratus OCT (Carl-Zeiss Meditec, Inc., Dublin, CA) that supplies high-resolution retinal imaging along with time-area (TD) OCT technology (Wollstein *et al*., 2005).

In view that the RNFL atrophy is among the initial signs of glaucoma sickness which shall be seen in the fundus images and many researchers attempt to investigate the visual look of RNFL. Previously, an effort to exploit fundus cameras for the purpose of glaucoma detection through the analysis of the RNFL appearance has been introduced first by Hoyt *et al*. (1973). In authors qualitatively published that the funduscopic indicators of the RNFL pattern present the previous objective proof of the RNFL atrophy present in the retina.

To improve clinical analysis, ophthalmologists regularly require large field-of-view and high spatial resolution OCT images. However, storage and transmission of such temporal and high spatial resolution OCT data consumes a vast amount of memory and communication bandwidth, which exceeds the boundaries of present clinical data archiving methods and generates a heavy burden for remote consultation and diagnosis. Hence, development of competent image compression strategies is the key to managing such large amounts of data. Most of the current compression techniques are on the basis of transform coding that as a first step does the projection of the input image into another domain and thereafter does the encoding of the modified coefficients. Perhaps the most well-known compression method is the joint photographic experts group (JPEG) (Wallace, 1991), which adopts the Discrete Cosine Transform (DCT) (Ahmed *et al*., 1974). JPEG compression scheme is simple, but does not perform well at low bit rates.

JPEG 2000 is a popular compression method, it based on the Discrete Wavelet Transform (DWT) (Skodras *et al*., 2001), which can better compress natural images (Burrus *et al*., 1998). Presently, Mousavi *et al*. (2014) compared the performance of the JPEG and JPEG 2000 compression methods for OCT images (Mousavi *et al*., 2014). However, the JPEG and JPEG 2000 are only designed for 2-D single-band images and do not take benefit of the correlations between neighboring slices in a typical 3D OCT volume. For 3D video or medical images, many other DWT based compression techniques are introduced (Schelkens *et al*., 2003). These methods utilize motion compensation or volume of interest coding to exploit the relations among the slices in the 3D volume.

In this study, DTCWT based OCT image compression is proposed. To improve the image contrast, OCT image is pre-processed using kaun filter. Secondly, the RNFL based texture features are extracted by using GLCM. And then improve the classification accuracy of proposed method the particular features are selected using PCA. Then, RNFL in OCT is segmented by IABC clustering algorithm. MNN is classified the glaucoma as normal, medium and severe. Finally, the medium and severe based OCT are compressed by DTCWT. The efficiency of the newly introduced system is statistically established with the aid of the efficiency evaluation.

LITERATURE REVIEW

Glaucoma is among the most general reasons of permanent blindness in human. For the reason that the preliminary symptoms are not evident, mass screening assists early prognosis within the big populace. Such mass screening requires an automated prognosis system (Raja and Gangatharan, 2015). The reward scientific approaches for Glaucoma detection most commonly incorporate manual observations and are in many instances invasive; therefore the progress of automated tactics for the extraction of features concerning Glaucoma aids their prognosis in a time potent and non-invasive manner. Glaucoma can permanently caused blindness though its prediction and treatment at previous stage can gradual down the development of the sickness.

The paper awarded preliminary outcome that were extra followed up through the identical crew in Muramatsu *et al*. (2010). The authors accelerated the earlier suggestion to evaluation and carried out analysis utilising higher dataset. Additionally, Prageeth *et al*. (2011) published a procedure for the purpose of detection of glaucoma utilizing intensity criterion also. Despite the fact that, the results looked to be hopeful, usage of the intensity criteria employed without help is ordinarily no longer a better solution.

Odstrcilik *et al*. (2014) presented a novel process to texture evaluation enabling measuring the thickness of the RNFL in largely used color fundus pix. The intention is to recommend a regression mannequin on the basis of various texture features potent for describing the alterations in the RNFL textural appearance involving the variants of the thickness of RNFL. The efficiency assessment makes use of OCT to be a gold usual modality for validating the process.

With the detection and analysis of some components of the retina, quite often the Optic Disc (OD), blood vessels and the the excavation placed within vascular bundle are useful in the detection of glaucoma. The traits most probably analyzed are the dimension of the cup/disc ratio and the neuro retinal rim thickness. The feature extraction approach depends simplest on the evaluation of morphological variations that may be detected within the OD, yet when the size of the excavation is within the initial stage of glaucoma (Fuente-Arriaga *et al*., 2014).

Different ophthalmic imaging technologies are used to seize images together with Fundus images, Confocal Scanning Laser Tomography (CSLT), Optic Coherence Tomography (OCT) for detection and prediction of glaucoma (Khalil *et al*., 2014). In recent times, digital imaging, equivalent to scanning of laser polarimetry scanning and optical coherence tomography, is used as a clinical tool to for the evaluation of the optic disc and nerve fiber layer in glaucoma detection. For quantitative analysis neural networks and fuzzy logic, the 2 complementary technologies are utilized on Stratus OCT information to become aware of glaucoma.

An automated image processing technique for detection of glaucoma is diagnostic tool to support ophthalmologist in mass screening of glaucoma suspects. The technique is established on the segmentation of OD and the optic cup and calculating the cup-to-disc ratio. In addition, to calculate the radius of OD and optic cup is used hough transform. For identify the glaucoma the vertical cup-to-disc ratio parameter is used signs inside fundus image (Dutta *et al*., 2014).

Continuously a computer performs a valuable position within the computerized detection of Glaucoma. As an effort a computerized threat comparison approach for glaucoma detection was developed. The system analyzes the patients' clinical data and the performances of the Nerve Fiber Layer Defects (NFLDs) detection. Afterwards the glaucoma risk assessment was evaluated. The clinical information as a rule incorporated is the systemic information, ophthalmologic information and proper and left retinal images. By using machine learning technique, a Glaucoma risk assesment algorithm was developed, synthetic neural network, Radial basis perform (RBF) network, k-nearest neighbour algorithm and support vector machine. However glaucoma risk assessment making use of this process and it's not assessed (Hatanaka *et al*., 2012).

Several methods are developed for usual calculation of cup to disc ratio by means of accurate detection of disc and cup and quantitative choice of their areas in retinal fundus images to identify glaucoma (Poshtyar *et al*., 2013). The medical systems used by ophthalmologists like HRT and OCT is high priced and time consuming. Thus there was a need to expand automatic system with a help of computer system which can distinguish glaucoma efficiently and in much less span of time. OD and optic cup are two main features that help in diagnosing glaucoma. Through a right segmentation algorithm constructed for segmenting OD and optic cup assists in detecting the disorder. Based on the adaptive threshold a new method is developed which is impartial of the quality of image and imperceptible to noise is utilized to segment optic cup, OD, Neuroretinal rim and cup to disk ratio is calculated to monitor glaucoma. An extra ocular parameter, rim to disk ratio can be considered in combination with CDR which gives extra reliability in identifying glaucoma and makes the system more strong (Agarwal *et al*., 2015).

Soe *et al*. (2014) proposed Fuzzy-K Nearest Neighbor (F-KNN) classifier is making use of finding angle closure glaucoma. 264 SS-OCT images had collected from 148 patients. It is achieved 98.11% of high accuracy rate. Finally, it illustrates that the new approach has talented potential to turn into a computer aided diagnostic tool for angle closure diagnosis of glaucoma disease.

Rajan and Ramesh (2016) they had used three classifier such as Naïve Bayes, k-Nearest Neighbour and Support Vector Machine for predicting the glaucoma disease. The experimental results shows that SVM classifier achieves good results when comparing with the NB and KNN. The accuracy rate is 90.75% and this proposed work yields sensitivity of 91.79% and specificity of 89.71%.

Anantrasirichai *et al*. (2013) detecting the Glaucoma by using retinal OCT. Classification has been done by using Support Vector Machine with the improvement of Principal Component Analysis. The thickness of the inner layer and texture are organized. Finally the results shows that texture features can be improved by using SVM classification accuracy is 4%.

Ricco and Chen (2009) presented efficient automated classification technique is used for differentiating the specific scan type. This algorithm distinguishes between the presence and absence of vessels which joining on the optic disc. They had tested the algorithm with 1015 scans of both normal and abnormal patients report. Finally by using Matlab the sensitivity of 100% and Specificity of 99.7%. This classifier is most secure to retinal pathologies and provide particular results suffering from Glaucoma.

PROPOSED METHODOLOGY

In this section, the proposed MNN based RNFL thickness measure for detecting glaucoma is discussed detailed in given below section. Image compression also discussed.

System overview: The overall process of proposed system is illustrated in Fig. 1. The step by step process is discussed given below:

- Pre-processing, for the removal of the speckle noise and improve the image efficiency using kuan filter.
- Feature extraction and selection is to extract the RNFL features for improving the classification accuracy.
- RNFL segmentation, the affected glaucoma pixels are segmented using IABC clustering.

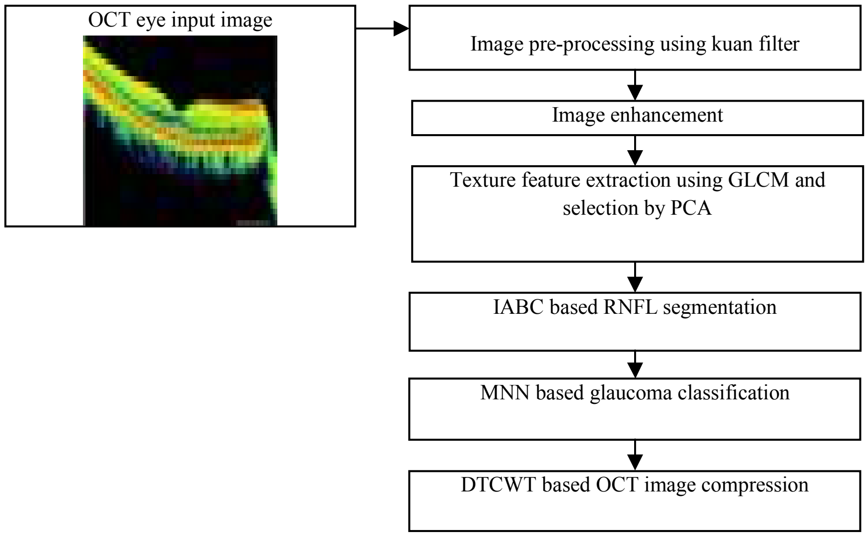

Fig. 1: Overall process of proposed system

- Glaucoma classification, the affected pixels classified using MNN.
- DTCWT is used to compress the OCT image to reduce the storage space.

Image Pre-processing: In this phase, the OCT image takes and processed to RGB. Then the image is pre-process because the image has some noises. Preprocessing is consists of denoising and enhancement steps. Denoising refers to the process employed for removing the noise that exists in the image; enhancement indicates a process used for increasing the image contrast. Here, the input OCT image has speckle noise. The speckle noises are generally degrades segmentation process and decreases image quality. It will increase the difficulties of image segmentation. So the speckle noise should be removed to achieve the accurate segmentation. In this research work, kuan filter is exploited for removing the speckle noise. The filter process is given below.

Kuan filter is used to denoising and smoothen the image without removing edges or sharp features in the images. In this process, the multiplicative noise model transforms into a signal-dependent additive noise model. After that, the minimum Mean Square Error (MSE) criterion is applied to the model. It makes no approximation to the original form, it can be measured as better to the Lee filter. Pre-processing resulting grey-level value R for the smoothed pixel is in Eq. (1):

$$R = I_c * W + I_m * (1 - W) \tag{1}$$

where,
I_c = Centre pixel in the filter window
I_m = Mean value of intensity within the window
W = Weighting factor

Image enhancement: In the second stage, image enhancement technique is used to improve a given image quality. So that the result obtained from image enhancement is extra useful than the original image for RNFL boundaries detection. This method is sharpens image features like edges, boundaries, or contrast for making an image with high quality for further processing. MATLAB image adjustment function is used to improve the image. It is generally increasing the intensity of images. By way of this image adjustment, the intensities will also be higher dispensed on the histogram. This converts areas of lessen nearby contrast to greater contrast. This is entire with the aid of effectively spreading out the most frequent intensity values.

Feature extraction using GLCM: Grey-Level Co-occurrence Matrix (GLCM) describes the spatial relationship between each intensity is representing changes between grey levels i and j at a particular displacement distance d and at a particular angle θ. Seven properties from GLCM are computed, i.e., energy measuring uniformity of local grey scale distribution; correlation measuring the joint probability of occurrence; entropy measuring randomness; contrast measuring the local variations; cluster shade that measures a category of pixels having similar values of grey level; homogeneity that measures the closeness corresponding to the distribution and the inverse difference moment measuring local minimal variations. In this proposed system, 28 features are extracted and also the average values of all angles utilized to obtain 7 features.

Feature selection using Principal Component Analysis (PCA): The PCA is for the reason of minimizing the huge data dimensionality. It consists of two phases; one is the training phase and another is test phase. OCT image recognition systems get the uniqueness of a test image on their memory. To find the feature vector used an image recognizer which is most similar to a test image given.

In training phase, the feature vectors are extracted for each image present to produced training set. Let Ω_1 is represented as an image1 training image and a pixel resolution are defined as M*N (M rows, N columns). To extracting the features of Ω_1 using PCA, the image is converted into a pixel vector Φ_1 during the concatenation of every M row into a solitary vector. After that, the length is corresponding to the vector Φ_1 will become M×N. The PCA algorithm is employed in the role of a dimensionality reduction strategy that does the transformation of the vector Φ_1 to a vector w_1 having a dimensionality d in which d << M * N.

For every training image Ω_i, these feature vectors w_i are computed and then stored. During the testing period, the feature vector w_j equivalent to the test image Ω_i and is computed employing PCA. For identifying the test image Ω_j, the similarities observed between w_j and every one of the feature vector w_i in the training set are calculated. The similarity seen between the feature vectors is calculated making use of Euclidean distance. The identity corresponding to the most similar w_i becomes the output from the image recognizer. When i = j, it indicates that the OCT image j has rightly identified, else if i ≠ j, it indicated that the OCT image j has done a misclassification.

Segmentation of RNFL: Here, Improved Artificial Bee Colony (IABC) clustering is used to discover boundaries of the RNFL. This algorithm grouping the glaucoma identical pixels region into one group and natural (normal) value of all pixels reward in that another group.

In ABC algorithm (Abu-Mouti and El-Hawary, 2012), D-dimensional is mentioned as the solution space of the problem, where D indicates the amount of optimized parameters. IABC is a selection mechanism for neighborhood of the candidate solutions in the Onlooker Bee (OB) stage. This selection mechanism was based on data shared by the Employed Bees (EB). By using the EBs is calculated average fitness value and this value are stored in to memory. So, the OBs select a neighbor's information from the memory.

The randomly selected site fitness value is given in the following Eq. (2):

$$avg_t^{pop} = \frac{1}{SN}\sum_{i=1}^{SN} fit_i \tag{2}$$

where, avg_t^{pop}→ an average fitness value of EBs population at iteration SN t and SN → number of EBs. EBs fitness values are tested with avg_k^{pop} and the solutions of EBs, which are better than avg_k^{pop}, are stored to the board. That board duration of solutions is calculated by:

$$D_i = k.fit_i \quad D_i = k.fit_i \tag{3}$$

where, K → a positive constant number, i→fitness value of ith EBs and D_i → waiting time on the memory of the solution and waiting time of the solutions is proportional to fitness values of EBS. Accordingly, neighbors for OBs (x_{kj} in Eq. (4)) are no longer choosen from the memory.

The volume of EB and OB are both SN (swarm of food sources), which is related to the amount of food sources. For every food source's locality, one EB is allocated to it. For each EB whose overall quantity is equivalent to the quantity of the food sources, obtained a new source in accordance with the following equation:

$$v_{ij} = x_{ij} + \Phi_{ij}\left(X_{ij} - X_{kj}\right) \tag{4}$$

where,

i, k = {1, 2,…, SN}

j = {1, 2,…., D}

Φ = A random generalized real number inside the range

[-1,1]. k indicates a randomly chosen index number in the Bee colony. Subsequent to the production of the new solution $\acute{v}$ = {$\acute{X}_{i1}$, $\acute{X}_{i2}$,…, $\acute{X}_{iD}$}, this solution compared to the original solution v = {X_{i1}, X_{i2},…,X_{iD}}. When the obtained solution is better than earlier solution, the bee remembers the new solution; or else it remembers the former solution. The OB chooses a food source based on the probability and it's provided in Eq. (5):

$$P_i = \frac{fit_i}{\sum_{j=1}^{SN} fit_j} \tag{5}$$

where,

fit_i = The fitness of the solution v

SN = The number of food sources locations

Later on, the OB looks for obtained new solution in the chosen food source mentioned in Eq. (5), the similar way as utilized by EB. During Scout Bee (SB) phase, as found food source fitness hasn't been enhanced for a specified number of trial or limit, it is discarded. This act signifies the negative feedback in IABC and that EBs food source happens to be a SB and constructs a random search through Eq. (6):

$$X_{id} = X_d^{\min} + r\left(X_d^{\max} - X_d^{\min}\right) \tag{6}$$

where, r = a → a random real number inside the range [0,1]. X_d^{min} and X_d^{max} → the lower and upper border in the d^{th} → the problems space of dimension. The fitness value the cluster centers are segmented efficiently. The pseudocode of IABC clustering is given below:

1. Initialize the parameters values. set the threshold value for SN (Population Size), 50% for employment bees, 50% for non-employment bees, randomly generate the Food Number (SN/2) feasible solutions, the maximum number of iterations is the maxCycle (MCN), the number of stagnation is the limit (during an iteration, if the optimal value does not improved after limit iteration, then reset the feasible solution)
2. The fitness fit_i of the population is evaluated in glaucoma image
3. For cycle = 1
4. Repeat
5. For each EB
   {
   New solution v_{ij} is produced by using Eq. (4)
   The fitness fit_i is calculated
   Greedy selection process is applied
   }
6. The probability values P_i is calculated for the solutions i by Eq. (5)
7. For each OB
   {
   A solution i is selected depending on P_i
   New solution v_{ij} is produced
   The fitness fit_i is calculated
   Greedy selection process is applied
   }
8. If an abonded solution occurred for the SB, then, replace it with a new solution which is randomly produced by using Eq. (6)
9. The best solution is stored until now
10. For cycle = cycle+1
11. Until cycle = MCN

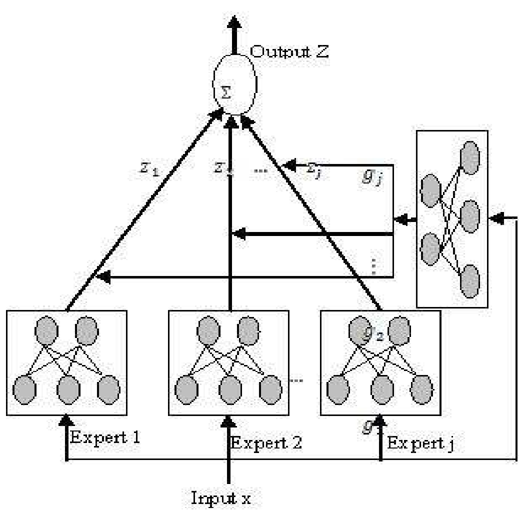

Fig. 2: Process of modular neural network architecture

Classification using MNN: In this research work, each module such as experts and gating networks received a distinct data set and the mixture of experts examines in Fig. 2. Every module, the gating network, consists of n input units, which describes the number of features. The output units determines the expert networks equals to the number of classification classes c, mean while gating network equals to the number of experts, say r. The data process is reliant over the random gradient algorithm, in which the objective function is given as:

$$-\ln\left(\sum_{j=1}^{r} g_j \exp\left(-\frac{1}{2}\left\|s-z_j\right\|^2\right)\right) \tag{7}$$

where, g refers to the output that is required for input x, $Z_j = XW_j$ refers to the output of jth exponent network:

$$g_j = \frac{\exp\left(u_j\right)}{\sum_j \exp(u_i)} \tag{8}$$

g_j→ the normalized output from the gating network, u_i → the total weighted input obtained by the output unit j of the gating network, also g_j → measured of the probability of choosing the expert j for a firm case. Every component in the collection associates with a modular neural network among the same structure and it simply defined as five experts with one gating network. Just as in the case corresponding to the multilayer perceptron, from the base classifiers decisions shows the ensemble at last combined by a majority voting.

Every module (entire of the gating network) is really a feed forward network and gets the actual input vector. Finally, the entire system output is the summation of z_j g_j.

Image compression using DTCWT: In this process, a gray scale OCT image is chosen for the purpose of compression. At first, the actual image undergoes decomposition by using Dual Tree Complex Wavelet Transform. The coefficients received are transformed by threshold for compression further applying arithmetic encoding in the process of entropy. Compression ratio is received from the image that is compressed.

Dual Tree Complex Wavelet Transform (DTCWT): Wavelet transform has disadvantages like Shift sensitivity, Absence of directional selectivity and Absence of phase information, hence it does not find its application in several domains. Dual Tree Complex Wavelet Transform (DTCWT) surpasses these above mentioned limitations and is illustrated in Fig. 3. It makes use of two unique discrete wavelet transform (Tree a, Tree b) along with low pass and high pass sub

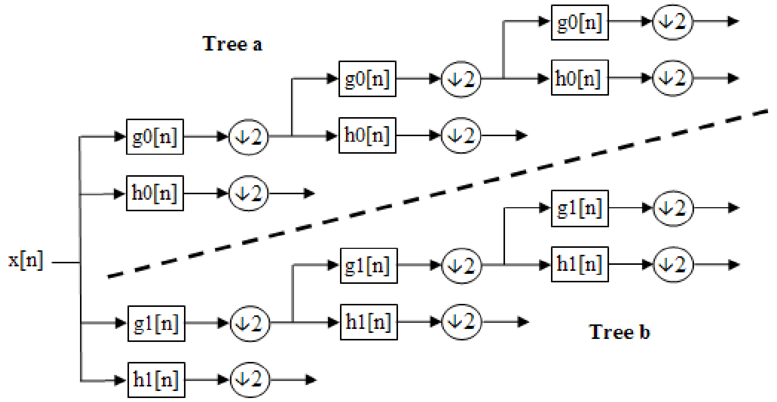

Fig. 3: Dual tree complex wavelet transform

band filters, for calculating the complex signal transform. Two DWT's can generate separately the real and imaginary coefficients, only if, both of the filters design are particularly diverse from each other. Upper DWT generates the real part whereas the lower DWT yields the imaginary part. In case both are the same, then there is no gain. The realization consists of two steps. Initially, the decomposition of an input image is carried out by two branches 'a' and 'b' in which the upper DWT is the Hilbert transform (approximate) connected with the lower DWT. Secondly, the same pass bands of the respective two sub bands are combined in a linear manner either through differencing or averaging.

In compression process, DTCWT is used over the input image that either brings the coefficients nearer or equivalent to zero. Additionally, the threshold λ also produces more zeros. λ is fixed and the value which is below λ is fixed to zero to produce more zeros in the hard thresholding, which, actually needs lesser space for storage and employing the entropy coding, the transmission tends to become more faster. Entropy coding is conducted by means of arithmetic coding for the purpose of compressing the image.

Arithmetic coding: Encoder process is one among the important steps in compression. The basic issue in lossless compression is the image decomposition into sequential events and then encoding of the events in the form of bits. Arithmetic coding substitutes the Huffman coding in the past few years due to its better compression ratio and performance for using in data compression. In this research work, arithmetic coding is utilized where the input symbol is substituted by a particular code in a file or message and this particular code is indicated by an integer number ranging between 0.0 and 1.0 of a real number. Short and long code words are allocated to more and less probable events correspondingly. This statistic tends to become accurate when the coding result attains the Shannon's entropy limit for the input symbols in a bigger sequence. Arithmetic coding comprises of three registers in the form of low, high and range.

RESULTS AND DISCUSSION

In this section, the proposed MNN classification and DTCWT classification method performance is assessed and its results of performance are compared to existing classification and compression methods. MATLAB 12 is used to simulate proposed algorithm. Performance is evaluated based on real time data set. It consists of 100 OCT images. Among them, 45 normal images and 55Abnormal images from various patients. The images in the database are RGB JPEG format images of size 689×329 pixels, which is converted into gray scale for this study. The proposed MNN classification is compared to existing scan pattern classification (Ricco and Chen, 2009) and DTCWT compression is compared to existing DWT (Schelkens *et al*., 2003).

Performance evaluation: The performance of glaucoma classification is evaluated with the parameters that follow:

- Sensitivity = TP/(TP+FN)
- Specificity = TN/(TN+FP)
- Accuracy = (TP+TN)/(TP+FN+TN+FP)

where,
TP = Determines true positive
FP = False positive
FN = False negative
TN = True negative

True Positive indicates the RNFL glaucoma which is rightly identified, True Negative indicates the glaucoma that is incorrectly identified, False Positive stands for the background RNFL that is rightly identified and False Negative indicates the RNFL pixels background that is incorrectly identified.

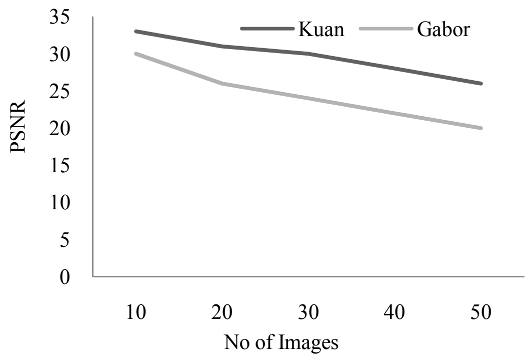

Fig. 4: PSNR comparison

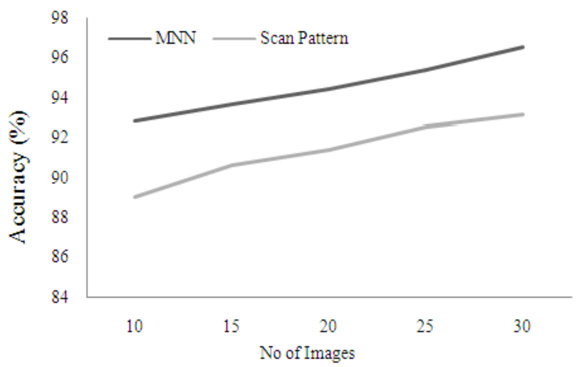

Fig. 5: Accuracy comparison

Peak of Signal-To-Noise Ratio (PSNR): The ratio between the most potential powers to the power of corrupting noise is called as PSNR. It affects the fidelity of its representation. Also it is defined as the logarithmic function of peak value of image and mean square error:

$$PSNR = 10\log_{10}(MAX_i^2 / MSE) \tag{9}$$

where, MSE is mean square error of an estimator is to quantify the difference existing between an estimator and the true value of the quantity being estimated:

$$MSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left[I(i,j) - K(i,j)\right]^2 \tag{10}$$

To measure the perceptual quality, after the noises are added to OCT images and then calculate the PSNR that is used to estimate the quality of the preprocessing OCT images in comparison with the original ones. The performance of the proposed kuan is compared with the existing gabor filter. The proposed scheme PSNR is higher when compare to existing technique is illustrated in Fig. 4.

Accuracy comparison: The proposed MNN produces 96.5% of accuracy rate shown in Fig. 5 which is much greater accuracy results than existing scan pattern. When the number of images increases the accuracy of the result increases. This approach produces high accuracy rate when compared to existing system.

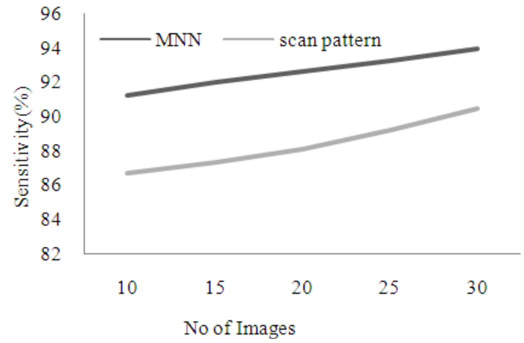

Fig. 6: Sensitivity comparison

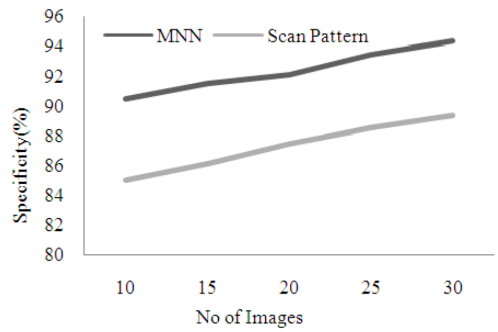

Fig. 7: Specificity comparison

Fig. 8: Compression ratio comparison

Sensitivity comparison: The proposed MNN produces 93.94% of sensitivity rate shown in Fig. 6 which is much greater sensitivity results than existing scan pattern. When the number of images increases the sensitivity of the result increases. This proposed approach produces high sensitivity rate when compared to existing system.

Specificity comparison: The proposed MNN produces 94.35% of specificity rate shown in Fig. 7 which is much greater specificity results than existing scan pattern. When the number of images increases the specificity of the result increases. This proposed approach produces high specificity rate when compared to existing system.

Compression ratio: Figure 8 illustrates that the compression ratio comparison results between proposed DTCWT and the available DWT. The results indicate that the proposed DTCWT gives high compression ratio thus exhibiting the good purity of retrieved image.

CONCLUSION

In this study, DTCWT based OCT image compression is proposed. First, the input image pre-processed by using kuan filter for remove speckle noise. It is then adopted through image enhancement by way of utilizing picture adjustment to expand the brightness of image. Secondly, the RNFL based texture features are extracted using GLCM. Then, RNFL in OCT is segmented by IABC clustering algorithm. After that the glaucoma is classified as normal, medium and severe by MNN. Finally, DTCWT is used to compress the OCT image. The experimental results exhibit that the proposed procedure attained 96.5% of high accuracy for glaucoma detection. The compression ratio is also high in proposed method. In future, classification can also be changed by different evolved procedure in an effort to segment the layers competently and efficient compression method will be focused.

REFERENCES

Abu-Mouti, F.S. and M.E. El-Hawary, 2012. Overview of Artificial Bee Colony (ABC) algorithm and its applications. Proceeding of the IEEE International Systems Conference (SysCon, 2012).

Agarwal, A., S. Gulia, S. Chaudhary, M.K. Dutta, C.M. Travieso and J.B. Alonso-Hernández, 2015. A novel approach to detect glaucoma in retinal fundus images using cup-disk and rim-disk ratio. Proceeding of the 4th International Work Conference on Bioinspired Intelligence (IWOBI, 2015), pp: 139-144.

Ahmed, N., T. Natarajan and K.R. Rao, 1974. Discrete cosine transform. IEEE T. Comput., C-23(1): 90-93.

Anantrasirichai, N., A. Achim, J.E. Morgan, I. Erchova and L. Nicholson, 2013. SVM-based texture classification in optical coherence tomography. Proceeding of the IEEE 10th International Symposium on Biomedical Imaging (ISBI, 2013).

Bock, R., J. Meier, L.G. Nyúl, J. Hornegger and G. Michelson, 2010. Glaucoma risk index: Automated glaucoma detection from color fundus images. Med. Image Anal., 14(3): 471-481.

Burrus, C.S., R.A. Gopinath and H. Guo, 1998. Introduction to Wavelets and Wavelet Transforms: A Primer. Prentice Hall, Upper Saddle River, NJ, USA.

Dutta, M.K., A.K. Mourya, A. Singh, M. Parthasarathi, R. Burget and K. Riha, 2014. Glaucoma detection by segmenting the super pixels from fundus colour retinal images. Proceeding of the International Conference on Medical Imaging, m-Health and Emerging Communication Systems (MedCom), pp: 86-90.

Fuente-Arriaga, J.A.D.L., E.M. Felipe-Riverón and E. Garduño-Calderón, 2014. Application of vascular bundle displacement in the optic disc for glaucoma detection using fundus images. Comput. Biol. Med., 47: 27-35.

Gabriele, M.L., H. Ishikawa, G. Wollstein, R.A. Bilonick, K.A. Townsend, L. Kagemann, M. Wojtkowski, V.J. Srinivasan, J.G. Fujimoto, J.S. Duker and J.S. Schuman, 2008. Optical coherence tomography scan circle location and mean retinal nerve fiber layer measurement variability. Invest. Ophth. Vis. Sci., 49(6): 2315-2321.

Hatanaka, Y., C. Muramatsu, A. Sawada, T. Hara, T. Yamamoto and H. Fujita, 2012. Glaucoma risk assessment based on clinical data and automated nerve fiber layer defects detection. Proceeding of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC, 2012). San Diego, California, USA, pp: 5963-5966.

Hoyt, W.F., L. Frisén and N.M. Newman, 1973. Fundoscopy of nerve fiber layer defects in glaucoma. Invest. Ophth. Vis. Sci., 12(11): 814-829.

Khalil, T., S. Khalid and A.M. Syed, 2014. Review of machine learning techniques for glaucoma detection and prediction. Proceeding of the Science and Information Conference. London, UK, pp: 438-442.

Mousavi, M., K. Lurie, J. Land, T. Javidi and A.K. Ellerbee, 2014. Telemedicine + OCT: Toward design of optimized algorithms for high-quality compressed images. Proceeding of the SPIE 8936, Design and Quality for Biomedical Technologies VII, pp: 10.

Mrugacz, M. and A. Bakunowicz-Lazarczyk, 2005. Optical coherence tomography measurement of the retinal nerve fiber layer in normal and juvenile glaucomatous eyes. Ophthalmologica, 219(2): 80-85.

Muramatsu, C., Y. Hayashi, A. Sawada, Y. Hatanaka, T. Hara, T. Yamamoto and H. Fujita, 2010. Detection of retinal nerve fiber layer defects on retinal fundus images for early diagnosis of glaucoma. J. Biomed. Opt., 15(1): 016021.

Odstrcilik, J. *et al*., 2014. Analysis of the retinal nerve fiber layer texture related to the thickness measured by optical coherence tomography. Proceeding of the VIP Image Conference. Funchal-Madeira, Portugal, 19: 105-110.

Parikh, R.S., S. Parikh, G.C. Sekhar, R.S. Kumar, S. Prabakaran, J.G. Babu and R. Thomas, 2007. Diagnostic capability of optical coherence tomography (Stratus OCT 3) in early glaucoma. Ophthalmology, 114(12): 2238-2243.

Poshtyar, A., J. Shanbezadeh and H. Ahmadieh, 2013. Automatic measurement of cup to disc ratio for diagnosis of glaucoma on retinal fundus images. Proceeding of the 6th International Conference on Biomedical Engineering and Informatics (BMEI 2013), pp: 24-27.

Prageeth, P.G., J. David and A. Sukesh Kumar, 2011. Early detection of retinal nerve fiber layer defects using fundus image processing. Proceeding of the IEEE Recent Advances in Intelligent Computational Systems (RAICS), pp: 930-936.

Raja, C. and N. Gangatharan, 2015. A Hybrid Swarm Algorithm for optimizing glaucoma diagnosis. Comput. Biol. Med., 63: 196-207.

Rajan, A. and G.P. Ramesh, 2016. Comparative study of glaucomatous image classification using optical coherence tomography. Int. J. Pharm. Sci. Rev. Res., 36(1): 277-280.

Ricco, S. and M. Chen, 2009. Classifiction of scan location in retinal optical coherence tomography. Proceeding of the IEEE International Symposium on Biomedical Imaging: From Nano to Macro (ISBI'09), pp: 1031-1034.

Schelkens, P., A. Munteanu, J. Barbarien, M. Galca, X. Giro-Nieto and J. Cornelis, 2003. Wavelet coding of volumetric medical datasets. IEEE T. Med. Imaging, 22(3): 441-458.

Schuman, J.S., T. Pedut-Kloizman, E. Hertzmark, M.R. Hee, J.R. Wilkins, J.G. Coker, C.A. Puliafito, J.G. Fujimoto and E.A. Swanson, 1996. Reproducibility of nerve fiber layer thickness measurements using optical coherence tomography. Ophthalmology, 103(11): 1889-1898.

Skodras, A., C. Christopoulos and T. Ebrahimi, 2001. The JPEG 2000 still image compression standard. IEEE Signal Proc. Mag., 18(5): 36-58.

Soe, N.N., J. Tian, P. Marziliano and H.T. Wong, 2014. Anterior chamber angle shape analysis and classification of glaucoma in SS-OCT images. J. Ophthalmol., 2014: 942367.

Wallace, G.K., 1991. The JPEG still picture compression standard. Commun. ACM, 34(4): 30-44.

Wollstein, G., J.S. Schuman, L.L. Price, A. Aydin, P.C. Stark, E. Hertzmark, E. Lai, H. Ishikawa, C. Mattox, J.G. Fujimoto and L.A. Paunescu, 2005. Optical coherence tomography longitudinal evaluation of retinal nerve fiber layer thickness in glaucoma. Arch. Ophthalmol., 123(4): 464-470.

Zhu, Y., P. Li, W. He, Y. Gao, Y. He and H. Ma, 2006. Layer structures localization in optical coherence tomography images. Proceeding of the IEEE International Symposium on Biophotonics, Nanophotonics and Metamaterials, pp: 50-53.