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Design & Development of Hybrid Algorithms for Glaucoma Detection in Humans–using Multi-Stage Discrete Wavelet Transform (3 Levels) & Principal Component Analysis

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ABSTRACT

In this paper, the overview of the design & development of hybrid algorithms for glaucoma detection in humans is presented using the concepts of the hybrid combination of multi-stage discrete wavelet transform & principal component analysis algorithms. Matlab tool is being used to develop the algorithms and observe the simulation results of the 2 stages after the hybrid combination of the multi-stage discrete wavelet transform & principal component analysis pattern concepts. The simulation results shows the effectiveness of the method proposed after seeing the results of DWT & the PCA.

Keywords: Glaucoma, LBP, LMBP

1. INTRODUCTION

The overall proposed block diagram w.r.t. the software implementation of the glaucoma detection proceeds is presented in shown in figure no. 4. Also, a brief exhaustive review of each and every block is being presented with its functionality & it has to be noted that the entire detection process is divided into 3 stages, viz., stage-I, stage-II & stage-III to arrive at the end product after stage-III, i.e., glaucoma detection. Here, in this paper, we have presented only the stage-II simulation results, whereas the stage-I was the outcome of another research paper.

2. DISCRETE WAVELET FEATURE ALGORITHM

Wavelet transforms have become increasingly important in image compression since wavelets allow both time and frequency analysis simultaneously. Feature Extraction Technique using Discrete Wavelet Transform for finding out the advanced features is one possible technique which can be used as the feature extraction technique in image processing to represent the image in its compact and unique form of single values or matrix vector. After extracting the cup and the disc by using LBP and LMBP it is given as an input to the wavelet algorithm and then principal component analysis is applied in order to extract the exact features and then we use GLCM since thisis a hybridisation method, we use multiple algorithms in order to extract the features so as to get the accurate resultsas shown in the Fig.1.

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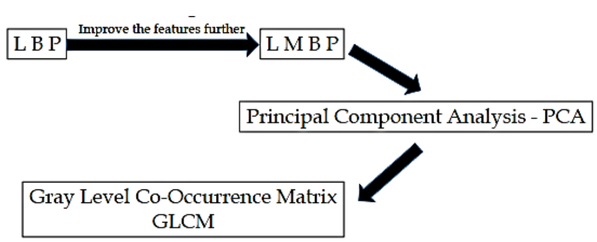

Fig. 1 : Flow chart of wavelet feature

Wavelet is a popular tool in image processing and computer vision. The range of applications very from compression, detection, recognition, image retrieval. Wavelet transform has unique features of space-frequency localization and multi resolutions. In mathematics, a wavelet series is a representation of a square-integrable (real- or complex-valued) function by a certain orthonormal series generated by a wavelet. This article provides a formal, mathematical definition of an orthonormal wavelet and of the integral wavelet transform. The wavelet transform is similar to the Fourier transform (or much more to the windowed Fourier transform) with a completely different merit function. The main difference is this: Fourier transform decomposes the signal into sines and cosines, i.e., the functions localized in Fourier space; in contrary the wavelet transform uses functions that are localized in both the real and Fourier space.

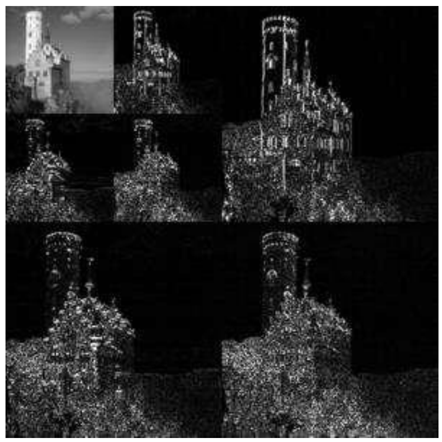

Fig. 2 : Example for 2D wavelet Transform

Generally, the wavelet transform can be expressed bythe following equation w.r.t. example for 2D wavelet transform can be modelled mathematically as
where the ***** is the complex conjugate symbol and the function ψ is some function. This function can be chosen arbitrarily provided that it obeys certain rules.

As it is seen, the Wavelet transform is in fact an infinite set of various transforms, depending on the merit function used for its computation. This is the main reason, why we can hear the term '*wavelet transform*' in very different situations and applications. There are also many ways how to sort the types of the wavelet transforms. Here we show only the division based on the wavelet orthogonality. We can use ***orthogonal wavelets*** for discrete wavelet transform development and ***non- orthogonal wavelets*** for continuous wavelet transform development. These two transforms have the following properties as

Property 1 : The discrete wavelet transform returns a data vector of the same length as the input is. Usually, even in this vector many data are almost zero. This corresponds to the fact that it decomposes into a set of wavelets (functions) that are orthogonal to its translations and scaling. Therefore, wedecompose such a signal to a same or lowernumber of the wavelet coefficient spectrumas is the number of signal data points. Sucha wavelet spectrum is very good for signal processing and compression, for example, as we get no redundant information here.

Property 2 : The continuous wavelet transform in contrary returns an array one dimension larger than the input data. For a 1D data we obtain an image of the time-frequency plane. We can easily see the signal frequencies evolution during the duration of the signal and compare the spectrum with other signals spectra. As here is used the non-orthogonal set of wavelets, data are highly correlated, so big redundancy is seen here. This helps to see the results in a more humane form.

$$F(a,b)=\int_{-\infty}^{\infty}\left(f(x)\psi^{*}_{(a,b)}(x)\right).dx$$

3. DISCRETE WAVELET TRANSFORM

The discrete wavelet transforms (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. In other words, this transform decomposes the signal into mutually orthogonal set of wavelets, which is the main difference from the continuous wavelet transform (CWT), or its implementation for the discrete time series sometimes called discrete-time continuous wavelet transform (DT-CWT).

The wavelet can be constructed from a scaling function which describes its scaling properties. The restriction that the scaling functions must be orthogonal to its discrete translations implies some mathematical conditions on them which are mentioned everywhere, e.g., the dilation equation. After introducing some more conditions (as the restrictions above does not produce unique solution), then we can obtain results of all these equations, i.e., the finite set of coefficients a_k that define the

The wavelet is obtained from the scaling function as N where N is an even integer. The set of wavelets then forms an orthonormal basis which we use to decompose the signal. Note that usually only few of the coefficients a_k are nonzero, which simplifies the calculations. There are several types of implementation of the DWT algorithm. The oldest and most known one is the Mallat (pyramidal) algorithm. In this algorithm two filters – smoothing and non-smoothing one – are constructed from the wavelet coefficients and those filters are recurrently used to obtain data for all the scales. If the total number of data $D = 2^N$ is used and the signal length is L, first $D/2$ data at scale $L/2^{N-1}$ are computed, then $(D/2)/2$ data at scale $L/2^{N-2}$, ….. up to finally obtaining 2 data at scale $L/2$. The result of this algorithm is an array of the same length as the input one, where the data are usually sorted from the largest scales to the smallest ones. Within Gwyddion, the pyramidal algorithm is used for computing the discrete wavelet transform

Discrete wavelet transform in 2D can be accessed using DWT module. Discrete wavelet transform can be used for easy and fast denoising of a noisy signal. If we take only a limited number of highest coefficients of the discrete wavelet transform spectrum, and we perform an inverse transform (with the same wavelet basis) we can obtain more or less denoised signal. There are several ways how to choose the coefficients that will be kept. Within Gwyddion, the universal thresholding, scale adaptive thresholding and scale and space adaptive thresholding is implemented.

When threshold for given scale is known, we can remove all the coefficients smaller than threshold value (hard thresholding) or we can lower the absolute value of these coefficients by threshold value (soft thresholding). DWT denoising can be accessed with *Data Process → Integral Transforms → DWT Denoise.*

4. CONTINUOUS WAVELET TRANSFORM

Continuous wavelet transform (CWT) is an implementation of the wavelet transform using arbitrary scales and almost arbitrary wavelets. The wavelets used are not orthogonal and the data obtained by this transform are highly correlated. For the discrete time series we can use this transform as well, with the limitation that the smallest wavelet translations must be equal to the data sampling. This is sometimes called Discrete Time Continuous Wavelet Transform (DT-CWT) and it is the most used way of computing CWT in real applications.

In principal the continuous wavelet transform works by using directly the definition of the wavelet transform, i.e. we are computing a convolution of the signal with the scaled wavelet. For each scale we obtain by this way an array of the same length N as the signal has. By using M arbitrarily chosen scales we obtain a field $(N \times M)$ that represents the time-frequency plane directly. The algorithm used for this computation can be based on a direct convolution or on a convolution by means of multiplication in Fourier space (this is sometimes called Fast Wavelet Transform).

The choice of the wavelet that is used for time- frequency decomposition is the most important thing. By this choice we can influence the time and frequency resolution of the result. We cannot change the main features of WT by this way (low frequencies have good frequency and bad time resolution; high frequencies have good time and bad frequency resolution), but we can somehow increase the total frequency of total time resolution. This is directly proportional to the width of the used wavelet in real and Fourier space. If we use the Morlet wavelet for example (real part – damped cosine function) we can expect high frequency resolution as such a wavelet is very well localized in frequencies. In contrary, using Derivative of Gaussian (DOG) wavelet will result in good time localization, but poor one in frequencies.

CWT is implemented in the CWT module that can be accessed with *Data Process → Integral Transforms → CWT*

The case for Wavelet transforms popularity can be observed due to its complete theoretical framework, low computational complexity, the great flexibility for choosing bases. Wavelets decompose complex signals into sums of basis functions – in this respect they are similar to other discrete image transforms. Be that Wavelet Feature as it may, wavelets are local in both recurrence and time and can dissect information at various scales or resolutions much superior to anything basic sine and cosine can. Similarly, as with the Fourier change, the purpose of wavelets isn't simply the wavelets; they are an unfortunate obligation. The objective is to transform the information of a signal into numbers – coefficients – that can be controlled, put away, transmitted, broke down, or used to remake the original signal. Not just the two major classes of wavelet changes - constant and discrete - however discrete changes can be excess, symmetrical, or biorthogonal. Every class contains countless potential outcomes.

Daubechies wavelet feature is been used in classification. Daubechies one of the brightest stars in the world of wavelet research, imaginary what are called efficiently supported orthonormal wavelets thus making discrete wavelet analysis practical. The names of the Daubechies family wavelets are printed dbN, where N is the order, and db the 'family name' of the wavelet.

Assets of Wavelet Transform will give an appropriate basis function for image handling. The assets of the wavelet transform are :

- Energy compaction : The ability to compress most of the signal's energy into a few transformation coefficients.
- The capability to capture and represent effectively low frequency components (such as image backgrounds) as well as high frequency transients (such as image edges).
- The variable resolution decomposition with almost uncorrelated coefficients.
- Progressive transmission : It facilitates the reception of an image at different qualities.

5. PRINCIPAL COMPONENT ANALYSIS (PCA)

Why PCA is needed in this juncture – the answer is : PCA condenses information from a large set of variables into fewer variables by applying some sort of transformation onto them. The image data has been chosen over tabular data so that the reader can better understand the working of PCA through image visualization. PCA is predominantly used as a dimensionality reduction technique in domains like facial recognition, computer vision and image compression. It is also used for finding patterns in data of high dimension in the field of finance, data mining, bioinformatics, and psychology. The multispectral image data is usually strongly correlated from one band to the other. The level of a given picture element on one band can to some extent be predicted from the level of that same pixel in another band. It should be noted in this context that the output of the previous section is given as input to this current section.

Principal component analysis is a pre-processing transformation that creates new images from the uncorrelated values of different images. This is accomplished by a linear transformation of variables that corresponds to a rotation and translation of the original coordinate system. Principal component analysis operates on all bands together. Thus, it alleviates the difficulty ofselecting appropriate bands associated with the band rationing operation. Principal components describe the data more efficiently than the original band reflectance values. The first principal component accounts for a maximum portion of the variance in the data set, often as high as 98%. Subsequent principal components account for successively smaller portions of the remaining variance.

Principal component transformations are used for spectral pattern recognition as well as image enhancement. When used before pattern recognition, the least important principal components are dropped altogether. This permits us to omit the insignificant portion of our data set and thus avoids the additional computer time. The transformation functions are determined during the training stage. Principal component images may be analysed as separate black and white images, or any three component images may be colour coded to form a colour composite. Principal component enhancement techniques are particularly appropriate in areas where little a priori information concerning the region is available.

6. IMAGE CLASSIFICATION

The overall objective of image classification is to automatically categorize all pixels in an image into land cover classes or themes. Normally, multispectral data are used to perform the classification, and the spectral pattern present within the data for each pixel is used as numerical basis for categorization. That is, different feature types manifest different combination of DNs based on their inherent spectral reflectance and emittance properties.

The term classifier refers loosely to a computer program that implements a specific procedure for image classification. Over the year's scientists have devised many classification strategies. From these alternatives the analyst must select the classifier that will best accomplish a specific task. At present it is not possible to state that a given classifier is "best" for all situations because characteristics of each image and the circumstances for each study vary so greatly. Therefore, it is essential that the analyst understands the alternative strategies for image classification.

The traditional methods of classification mainly follow two approaches: unsupervised and supervised. The unsupervised approach attempts spectral grouping that may have an unclear meaning from the user's point of view. Having established these, the analyst then tries to associate an information class with each group. The unsupervised approach is often referred to as clustering and results in statistics that are for spectral, statistical clusters. In the supervised approach to classification, the image analyst supervises the pixel categorization process by specifying to the computer algorithm; numerical descriptors of the various land cover types present in the scene.

To do this, representative sample sites of known cover types, called training areas or training sites, are used to compile a numerical interpretation key that describes the spectral attributes for each feature type of interest. Each pixel in the data set is then compared numerically to each category in the interpretation key and labelled with the name of the category it looks most like. In the supervised approach the user defines useful information categories and then examines their spectral separability whereas in the unsupervised approach he first determines spectrally separable classes and then defines their informational utility.

It has been found that in areas of complex terrain, the unsupervised approach is preferable to the supervised one. In such conditions if the supervised approach is used, the user will have difficulty in selecting training sites because of the variability of spectral response within each class. Consequently, a prior ground data collection can be very time consuming. Also, the supervised approach is subjective in the sense that the analyst tries to classify information categories, which are often composed of several spectral classes whereas spectrally distinguishable classes will be revealed by the unsupervised approach, and hence ground data collection requirements may be reduced. Additionally, the unsupervised approach has the potential advantage of revealing discriminable classes unknown from previous work. However, when definition of representative training areas is possible and statistical information classes show a close correspondence, the results of supervised classification will be superior to unsupervised classification.

7. Unsupervised Classification

Unsupervised classifiers do not utilize training data as the basis for classification. Rather, this family of classifiers involves algorithms that examine the unknown pixels in an image and aggregate them into a number of classes based on the natural groupings or clusters present in the image values. It performs very well in cases where the values within a given cover type are close together in the measurement space, data in different classes are comparatively well separated.

The classes that result from unsupervised classification are spectral classes because they are based solely on the natural groupings in the image values the identity of the spectral classes will not be initially known. The analyst must compare the classified data with some form of reference data (such as larger scale imagery or maps) to determine the identity and informational value of the spectral classes. In the supervised approach we define useful information categories and then examine their spectral separability; in the unsupervised approach we determine spectrally separable classes and then define their informational utility.

There are numerous clustering algorithms that can be used to determine the natural spectral groupings present in data set. One common form of clustering, called the '*k*- means' approach also called as ISODATA (Interaction Self-Organizing Data Analysis Technique) accepts from the analyst the number of clusters to be located in the data. The algorithm then arbitrarily "seeds", or locates, that number of cluster centers in the multidimensional measurement space. Each pixel in the image is then assigned to the cluster whose arbitrary mean vector is closest.

After all pixels have been classified in this manner, revised mean vectors for each of the clusters are computed. The revised means are then used as the basis of reclassification of the image data. The procedure continues until there is no significant change in the location of class mean vectors between successive iterations of the algorithm. Once this point is reached, the analyst determines the land cover identity of each spectral class. Because the K-means approach is iterative, it is computationally intensive. Therefore, it is often applied only to image sub-areas rather than to full scenes.

8. SUPERVISED CLASSIFICATION

Supervised classification can be defined normally as the process of samples of known identity to classify pixels of unknown identity. Samples of known identity are those pixels located within training areas. Pixels located within these areas term the training samples used to guide the classification algorithm to assigning specific spectral values to appropriate informational class. The basic steps involved in a typical supervised classification procedure are illustrated on Fig. The training stage Feature selection
of appropriate classification algorithm Post classificationsmoothening Accuracy assessment.

PCA is generally used to get rid of the less discriminative features and to obtain the exact features here in the process the wavelet features output is given as an input to the PCA here the exact features of the effected region are extracted. In the feature vector all the features are said to be independent, we can simply reject the least discriminative features from this vector. The least discriminative features can be eliminated by sing different approaches. However, in reality, each feature depends on the other. So, removing one feature can remove more information so we give a solution to this problem by using PCA as a decorrelation method.

9. IX PCA AS A DE-CORRELATION METHOD

Features are usually correlated. for an example, let us consider the case where we have to classify an image based on the red, blue and green colour of each pixel in an image to classify the image (e.g., detect dogs versus cats). Red light sensitive sensors can also capture some blue and green light. Similarly, blue light sensitive sensors can capture green and red light. As a result, the all the colours of a pixel are statistically correlated and contain the information of one another.

Therefore, if we eliminate the *R* component from the feature vector, we are also removing the information about the Green and Blue channels. So, before eliminating the features, we should transform the features space in such a way that all the underlying components that are uncorrelated are removed. The multispectral image data is usually strongly correlated from one band to the other. The level of a given picture element on one band can to some extent be predicted from the level of that same pixel in another band.

Principal component analysis is a pre-processing transformation that creates new images from the uncorrelated values of different images. This is accomplished by a linear transformation of variables that corresponds to a rotation and translation of the original coordinate system. Principal component analysis operates on all bands together. Thus, it alleviates the difficulty of selecting appropriate bands associated with the band rationing operation. Principal components describe the data more efficiently than the original band reflectance values. The first principal component accounts for a maximum portion of the variance in the data set, often as high as 98%. Subsequent principal components account for successively smaller portions of the remaining variance.
Principal component transformations are used for spectral pattern recognition as well as image enhancement. When used before pattern recognition, the least important principal components are dropped altogether. This permits us to omit the insignificant portion of our data set and thus avoids the additional computer time. The transformation functions are determined during the training stage. Principal component images may be analysed as separate black and white images, or any three component images may be colour coded to form a colour composite. Principal component enhancement techniques are particularly appropriate in areas where little a priori information concerning the region is available. Wavelet features output is given as an input to the PCA.

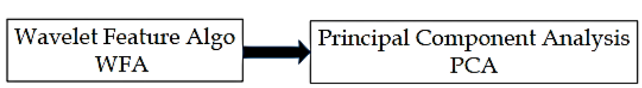

Fig. 3 : Flow chart of the PCA

Finally, the output of the stage-II is given as input to the next stage-III which is the outcome of another research paper.

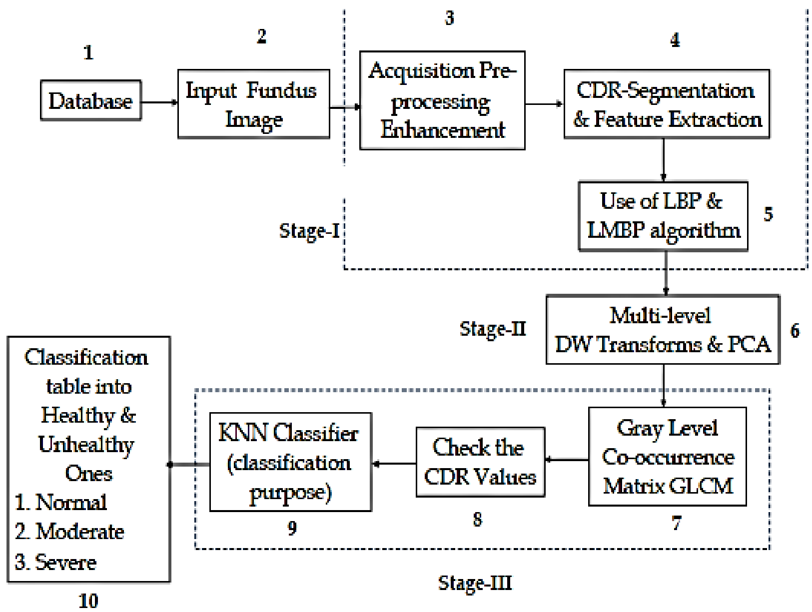

Fig. 4 : Proposed block-diagram of the hybrid representation of glaucoma detection using LBP, LMBP, DWT, PCA, GLCM & *k*-NN

10. SIMULATION RESULTS

A program (.m code) along with subroutines & function calls is developed using the Matlab tool & the developed main program is run for different fundus images as the input & the results are observed for various cases of glaucoma, viz., normal case (case-1), moderate case (case-2) & severe case (case-3) for one particular set of images, say, image_1, image_2, image_3 …. Set 1. The exercise is repeated for another set of 2 groups set 2 & set 3, i.e., 6 images. To start with fundus images, viz., image_1.jpeg, image_2.jpeg & image_3.jpeg from the set 1 are given as inputs to the created hybrid algorithm one after other & the simulations results are observed till the occurrence of the 3-stage wavelet transforms along with the PCA outputs. Essentially, the investigation is completed for the remaining 51 pictures (27 sets) which are available in the considered database

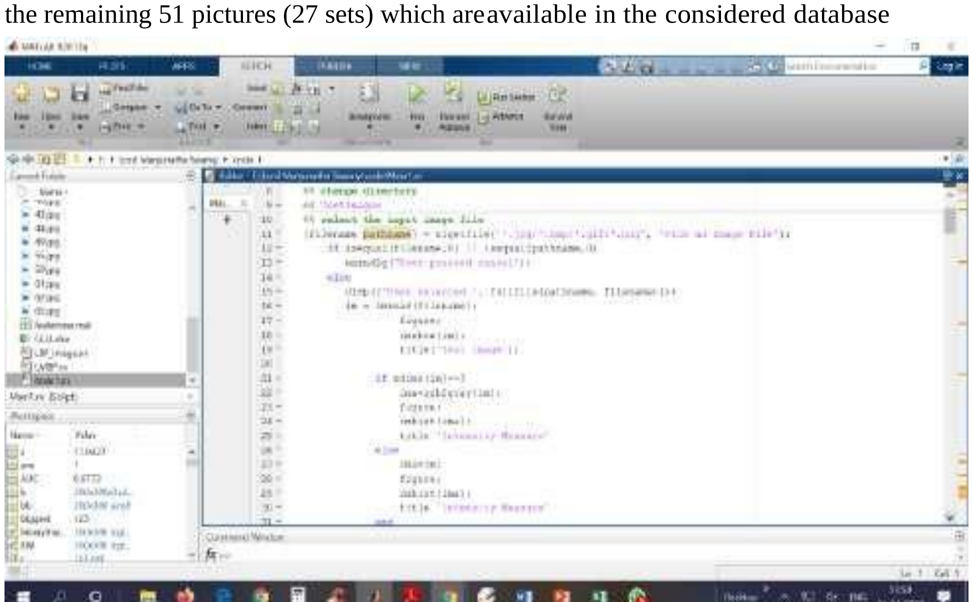

Fig. 5 : Matlab file showing the hybrid algorithm

The following processes are to be carried out for one setof image from the database

Set – 1 : image_1

Case 1 : Simulation results showing normal glaucoma

- Select the test sample (give input from the database)
- Histogram output : we get the intensity of the coloursof the image
- We extract the disc image as we have to find theCDR ratio taking it as the ROI
- We extract the cup : in order to find the cup to discratio.
- The boundary of the disc
- All the parameters in single image
- LBP image : The grey scale image is shown in thefigure below
- The LMBP image: the figure shows local multilevelbinary pattern extracted image
- We obtain the first level wavelet feature
- Below figure shows second level wavelet feature
- Figure showing the 3rd level wavelet feature

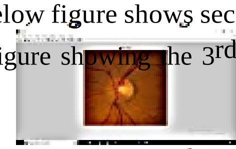

Fig. 6 : test sample

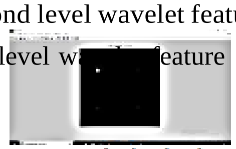

Fig. 7 : The first level wavelet feature

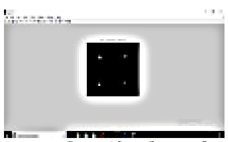

Fig. 8 : the 3rd level wavelet feature

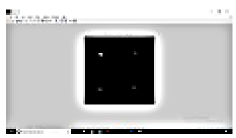

Fig. 9 : Second level wavelet feature

Set – 1 : image_2

Case 2 : Simulation results showing the moderate glaucoma

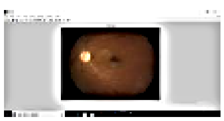

Fig. 10 : Test sample

Fig. 11 : First level wavelet

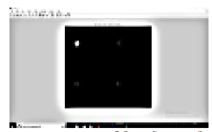

Fig. 12 : Second level wavelet

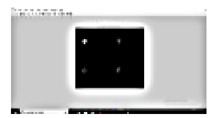

Fig. 13 : Third level wavelet

Set – 1 : image_3

Case 3 : Simulation results showing the severe glaucoma detection

Fig. 14 : Test sample

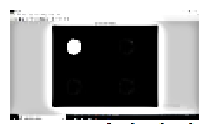

Fig. 15 : The first level wavelet

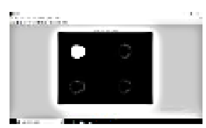

Fig. 16 : The second level wavelet

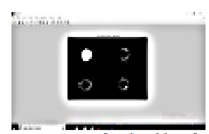

Fig. 17 : The third level wavelet

11. CONCLUSIONS

In this section, we present the concise result (outcome or the end-result), i.e., the simulation results w.r.t. the software implementation of the glaucoma detection work done. Research was carried out on the development of bio medical image processing algorithms w.r.t. the diagnosis & detection of the glaucomatic disease in human beings. To start with, an extensive background research was carried out on the chosen research topic. A number of reference text books, conference & journal research papers which covered the basic & fundamental concepts relating to the theoretical aspects, practical aspects, hospital aspects and w.r.t. the implementation point of view were collected and a brief study was carried out.

Codes were developed in Matlab for all the stage-II ofthe proposed block diagram shown in the Fig. 4 of our contributory work, the program was run & the results were observed for various cases healthy-normal (non-glaucomatic), unhealthy-moderate, severe (glaucomatic) cases. Only 3 case studies (normal, moderate & severe) were carried out of 60 images from the database for a particular set of images. Like this, another 2 sets of case studies was conducted. It has to be noted in this context that CDR concept was used for the glaucoma detection, actually the simulation results till the output of the DWTs & the PCA algo is shown here for the sake of convenience as this is the highlight of the paper. The Figs. 6-17 shows the effectiveness of the method proposed by us.

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