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Automated classification of coronary artery disease using discrete wavelet transform and back propagation neural network

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An automated classification of coronary artery disease using discrete wavelet watershed transform and back propagation neural network has been proposed which basically segments the blood vessels of the coronary angiogram image as a first step, which in turn involves various stages such as pre-processing, image enhancement, and segmentation using discrete wavelet transform and watershed transform along with morphological operations. Pre-processing is done to remove the noise using the bicubic interpolation method followed by Daubechies 4 discrete wavelet transform and Weiner filtering. Further, image enhancement is done to improve the quality of the image using the histogram equalization technique. Auto thresholding is done to segment the edges of the blood vessel accurately and efficiently using distance and watershed transforms followed by normalization and median filtering. Finally, morphological operations are performed to remove the noise due to segmentation. Features such as area, mean, standard deviation, variance, brightness, diameter, smoothness, compactness, skewness, kurtosis, eccentricity and circularity are extracted from the segmented coronary blood vessel to train the neural network using back propagation network. Thus, the system is able to achieve 93.75% normal classification and 83.33% abnormal classification. Also, 90% efficiency is achieved in classifying Type 1 and 92% efficiency is achieved in classifying Type 2 stenosis at a learning rate of 0.7 and Type 1 classification efficiency of 85% and Type 2 classification of 89% has been achieved for 50 hidden units of the neural network.

Key words: Coronary artery disease, discrete wavelet transform, watershed transform, morphological operations, back propagation neural network.

INTRODUCTION

Medical images such as coronary angiogram images account for a large portion of noise. There is a real challenge to segment such blood vessels. Angiography is a procedure to observe the blood vessels of a human being and further investigation is carried with the help of angiograms which detects the edges of the blood vessel.

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Blood vessel detection is an important diagnostic concept of image segmentation, which detects the edges of the angiographic blood vessels (Albert, 2006; Rice et al., 2000; Bouchet et al., 2007; Cemil and Francis, 2004; Nain et al., 2004; Lacoste et al., 2006; Brieva et al., 2005; Suri et al., 2002; Nyual et al., 2000; Lorigo et al., 2001; Lo et al., 2006; Sarry et al., 2001; Hassouna et al., 2003; Wink et al., 2004; Saha et al., 2000; Rafael et al., 2002; Chan et al., 2000; Espin et al., 2004; Zhou et al., 2006).

Jean et al. (2008) have used the application of minimal surfaces and Markov random fields as models and applied to the region adjacency graph of the watershed transform to segment the liver tumors. The researcher attempted to segment the relevant tumors from the liver image. Although the researcher did not segment the blood vessels of the angiogram image, but it is understood that unsupervised watershed transform along with Markov model is applied. Jayadevappa et al. (2009) developed a hybrid segmentation model based on Watershed and Gradient Vector flow (GVF) for the detection of the brain tumor. Generally the GVF suffers from a very high computational requirements and sensitive to noise. These are overcome by the integrated method which makes use of the watershed algorithm.

Ning et al. (2007) proposed a new algorithm which combines the watershed transform (Nassir, 2005) and level set method in order to extract the accurate boundary of the vessels. The researcher demonstrated the cost time which mainly depends on the number of pre segmented regions. However, performance of the system could be improved only if some prior information and distinguishable features are included and the researcher did not carry any performance evaluation. Pinaki and Dibyendu (2012) proposed an easy and simple method to overcome over segmentation by using the distance transforms and image smoothing of the morphological techniques (Sun et al., 2007; Deng and Heijmans, 2002; Tsair et al., 2009, 2003; Wong et al., 2005; Weili et al., 2010) along with watershed for segmentation. Plot with the number of pixels before and after smoothing was done to prove the performance of the system and testing was performed only on color images and not on medical images which is one of the limitations.

Ishita and Monisha (2012) proposed a new method for brain tumor segmentation using watershed (Jean et al., 2008) and edge detection algorithm in HSV color model. Initially the RGB image is converted into HSV color image and watershed algorithm is applied to each region after contrast enhancement which is then followed by canny edge detection. Finally all the three images are combined to get the segmented image. However, the performance of the system was not evaluated using any parameter. Yugander and Sheshagiri (2012) developed an improved watershed algorithm and modified level set method. The over and under segmentation problems were overcome by using dual tree complex wavelets and modified watershed based on Wasserstein distance. This method was used to extract the finger print from the original image and not for segmentation of the blood vessels and the performance of the system was not evaluated. Also, the system involves complex wavelets which itself is complex.

Qing et al. (2004) and Li et al. (2006) evaluated the performance of the watershed algorithm by analyzing the binary images and comparing them against different distance transforms. The researcher concluded that the Watershed algorithm is very effective for grey level segmentation of medical images. The researcher concluded that the chessboard distance transform performed well as against the Euclidean distance. Ghassan et al. (2009) pointed out that although watershed transformation is generally used for segmentation it is limited due to over segmentation and sensitivity to noise. However, these drawbacks were overcome by enhancing the prior shape and appearance knowledge. The problem of over segmentation was overcome by using clustering namely k-means segmentation and noise is removed or suppressed by computing the mean intensity of each segment. However, the researcher did not evaluate the performance of the system proposed and it involves complex algorithm.

Nassir et al. (2006) has combined K-means clustering, watershed and difference in strength (DIS) for segmentation. Although the proposed method overcomes the over segmentation there is no valid performance evaluation done. Zulong and Kaiqiong (2010) used contour based segmentation which in turn uses the morphological operations (Qing et al., 2004; Chan et al., 2000; Shoujun et al., 2009; Sidahmed et al., 2013) were used to detect the edges rather than using the gradient or gray level intensity, whereby the problems due to inhomogeneity is overcome. However, the researcher did not carry any coronary quantitative or statistical analysis to prove the efficiency of the system (Hernandez et al., 2000; Morteza et al., 2011; Schrjver et al., 2002; Pascal et al., 2006; Yan et al., 2005; Kobashi et al., 2000; Mukhopadhyay et al., 2003; Zhou et al., 2008; Chan and Vese 2001; Law et al., 2001; Yu, 2002).

Chih-Yang and Yu-Tai (2005) introduced the extraction of coronary angiogram blood vessels from the digital angiographic images. The researchers used three important steps to segment or extract the coronary angiogram blood vessel, they are namely, background elimination and noise removal, blood vessel enhancement and blood vessel segmentation from the coronary angiogram image. In the first stage, the researcher applied a temporal fourier transform followed by a high pass temporal filtering, which allows only the low-frequency terms, followed by inverse fourier transform. The transformed image so formed will not have any unwanted background, however, contains some spikes or noise, which may be due to isolated noise which cannot be detected and removed by using the fourier transform as it is based on the pure frequency domain. Hence to remove the isolated noise Discrete Wavelet Transform (DWT) (Ali et al., 2009; Elly, 2011; Jorge et al., 2003; Yu, 2002; Zulong et al., 2010; Tang et al., 2006) is applied. A three level decomposition was employed and the LLL sub-band region will consist of the features pertaining to the blood vessel. Thresholding is applied to preserve the edge information and finally Inverse Discrete Wavelet Transform (IDWT) is applied.

In the second stage, blood vessel enhancement is done using 72 matched filters (Hoover et al., 2000) and is projected onto the xy plane, followed by blood vessel segmentation, based on clustering analysis using a stencil mask. Further, histogram analysis is carried with thresholding and 18-adjacency clustering to segment the coronary angiogram blood vessel. The method used is very complicated involving two transforms, 72 matched filters, masking and thresholding. Also, the overall execution time was less than 3 min. However, the researcher did not carry any coronary quantitative or statistical analysis to prove the efficiency of the system.

Wenwei et al. (2010) proposed new segmentation method which is based on the transition region extraction (Liang et al., 2001). The researcher used 6 Gaussian matched templates to basically enhance the input coronary angiogram image followed by local complexity method. Segmented image was obtained by applying thresholding to the histogram of the transition region (Yao et al., 2008; Rivest, 2004; Socher et al., 2008; Shoujun et al., 2009) which outperformed the top-hat method. However, the researcher neither did not carry any coronary quantitative or statistical analysis to prove the efficiency of the system nor computed the overall execution time.

Santhiyakumari and Madheswaran (2010) have proposed a method to categorize the carotid artery subjects into normal and diseased subjects namely, cerebrovascular and cardiovascular diseases. For each and every pre-processed ultrasound carotid artery image, contours are extracted using contour extraction techniques. Multilayer Back Propagation Network (MBPN) system has been developed for categorizing the carotid artery subjects. The obtained results showed that MBPN system provides higher classification efficiency, with minimum training and testing time.

Sidahmed et al. (2013) have proposed an algorithm to produce a 85.5% classification accuracy in the diagnosis of Coronary Artery Disease (CAD), in which Genetic Algoirthm (GA) generates in each iteration a subset of attributes that will be evaluated using the Bayes Naïve (BN) based feature selection in the second step of the selection procedure. Thus, the assest of the algorithm is then compared with the Support Vector Machine (SVM), Multi-Layer Perceptron (MLP) and C4.5 decision tree algorithm. The results of classification accuracy for those algorithms are 83.5, 83.16 and 80.85% respectively.

Brieva et al. (2005) evaluated four segmentation algorithms for coronary angiogram images. The four algorithms were namely wavelets, snakes, level sets and dynamic threshold (Masoomeh et al., 2009; Mohammed et al., 2011). Here, a multi-resolution wavelet method was employed which consists of filter banks in turn consisting of one dimensional wavelet functions. A set of five filters are applied and segmented based on thresholding. The researcher used mean specificity and mean sensitivity for evaluating the performance of the system. However, the researcher did not carry any other coronary quantitative or statistical analysis to prove the efficiency of the system nor computed the overall execution time. Thus, the system looks complicated with filter banks and set of five filters.

PROPOSED METHOD

From the literature review discussed in introduction, it is clearly evident that the limitations of the watershed algorithm are overcome by enhancing various other techniques from the literature. Also, it is found that the watershed algorithm along with some other techniques is used for the segmentation of medical images such as liver, retina and brain, but is not done for the angiographic images of the heart. In the literature, the researchers have used wavelet discrete transform for suppressing noise and to get more information on the edges of the medical image for segmentation. Thus, the proposed method integrates the watershed algorithm and discrete wavelet transform (Tsair et al., 2009, 2003) which overcomes the limitations of the watershed algorithm along with the morphological operations and drawbacks mentioned in the introduction. Furthermore, it automatically classifies the segmented image into stenosis Type 1 or 2 CAD using the back propagation neural network.

Figure 1 shows the flow diagram of the automated classification of the integrated segmented blood vessel. The proposed automated classification and integrated coronary angiogram image segmentation algorithm using the Discrete Wavelet transform and Watershed Transform (DWWSHD) consists of five major steps, namely:

Step 1: Image pre-processing
Step 2: Image enhancement
Step 3: Image segmentation
Step 4: Feature extraction
Step 5: Classification of CAD

(i) Image pre-processing

In this step, first the given coronary angiogram image is resized to 256 x 256. Then, pre-processing is done using the following steps as shown in Figure 2 to produce sharper images of the input coronary angiogram image. Also, it removes noise acquired in the angiogram image.

Bicubic interpolation method

In order to produce sharper input coronary angiogram images, the bicubic interpolation method is adopted in the pre-processing stage. In the bicubic interpolation method the output pixel is obtained as a weighted average of the pixels in the nearest 4-by-4 neighbourhood followed by noise removal and background elimination.

Discrete wavelet transform

Wavelet transform is taken to extract the features initially. After pre

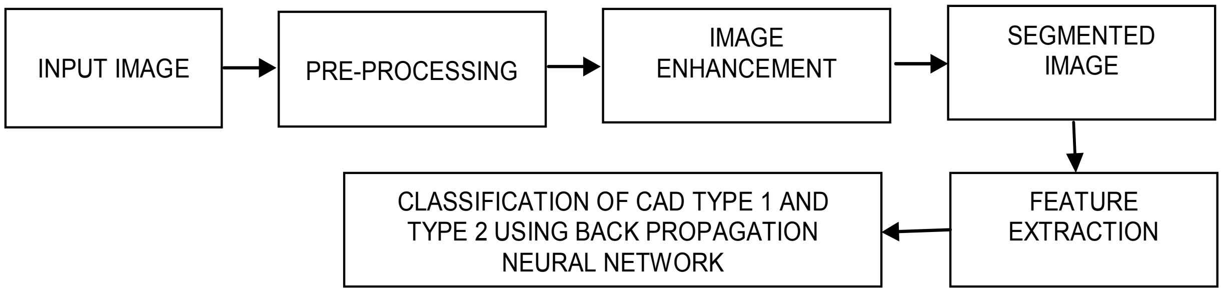

Figure 1. Proposed automated classification method.

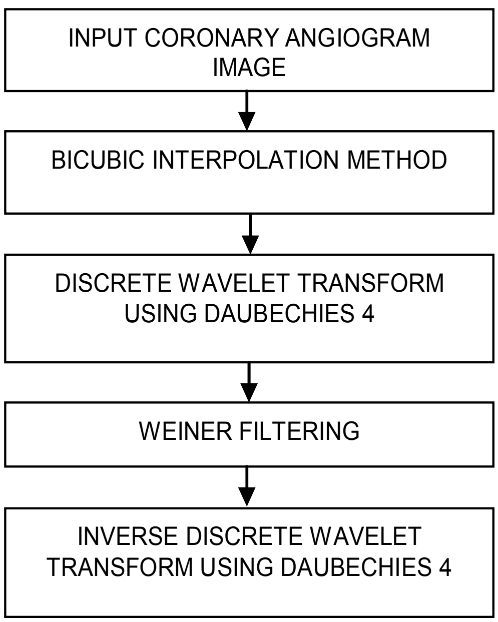

Figure 2. Image pre-processing.

processing, the coronary angiogram images do contain some noise or spikes, which are due to the presence of the isolated noise. These noises are usually not detected and removed by the frequency domain filters or fourier transforms. Hence a wavelet transform is applied after pre-processing which is done to remove the noise.

The DWT is applied to divide the given Coronary Angiogram Image (CAI) into four bands, the Low Low [LL], Low High [LH] , High Low [HL] and High High [HH] band. The DWT decomposes the given image based on the scale wavelet coefficients, which represent the noisy signals of the image contained in all the bands except the LL, which retains the features or the edge information of the coronary angiogram image.

A wavelet transform normally consists of a pair of high pass and low pass filters as shown in Figure 3, which are used to decompose the given coronary angiogram image into the low frequency and high frequency components respectively, according to the different number of levels. The decomposed coronary angiogram image is further down (D) sampled by 2 to get the approximation coefficients (cA) and detailed coefficients (cD), which are said to be called as the DWT wavelet coefficients. However, the image can be reconstructed again using the Inverse Discrete Wavelet Transform (IDWT), which is so called as the reconstruction process. Normally, the input coronary angiogram image is divided into four regions, namely:

(a) LL – This sub band is obtained by using two low-pass filters,
(b) LH and HL – These two sub bands are obtained by using one low-pass filter and one high-pass filter, and
(c) HH – This sub band is obtained by using two high-pass filters.

After the first level of decomposition, the LL sub band is decomposed again using the same pair of low-pass filter and high-pass filter to perform n-stage discrete wavelet transform. Thus scale based decomposition is obtained by the wavelet transform in which the noise is represented by the finer scaled wavelet coefficients. The LL sub band does not contain any noise while all other sub bands do contain noise. However, the coefficients of such scales represent the edge information, which must be maintained by selecting a threshold to remove the noise. Thus, the unwanted noise is removed while the important local features of the coronary angiogram blood vessel is retained that is, the edge information is preserved.

In the proposed integrated method, the Daubechies 4 discrete wavelet transform (Elly, 2011) is applied with periodization to the coronary angiogram image. It produces the smallest length wavelet decomposition and the same mode of periodization is applied for IDWT to ensure perfect reconstruction. The Daubechies 4 wavelet transform is comparatively distinct from Haar wavelets because the scaling signals and wavelets produced are due to average's and differences from the signals. It conserves the signals energy and redistributes in a compact form.

Weiner filtering

Usually interpolation tends to increase the mean square error and hence in order to minimize it, the Weiner filtering approach is employed. It performs very well on the edges of the given coronary angiogram images, which is applied before taking the IDWT and after the DWT. Thus Weiner filtering is used to detect the edges of the given coronary angiogram blood vessel.

Algorithm

(a) Perform the DWT of the given input coronary angiogram image.
(b) Preserve the edge information of the LL band by applying Weiner filtering.
(c) Perform IDWT of the modified image from step b.

This produces the edge enhanced image, which is sharper than the original input coronary angiogram image in which more details can be seen clearly. Thus, the Daubechies 4 wavelet transform is used to preserve the edge and detailed visibility information, which is the

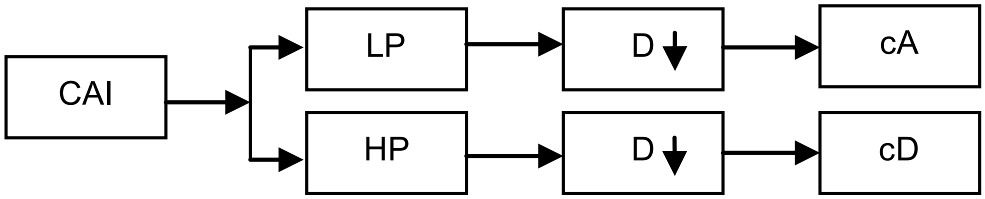

Figure 3. Single level wavelet decomposition.

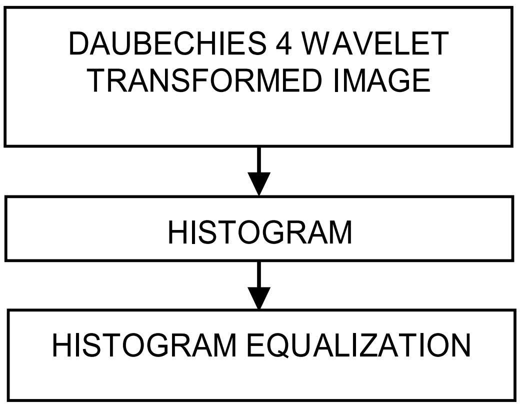

Figure 4. Image enhancement.

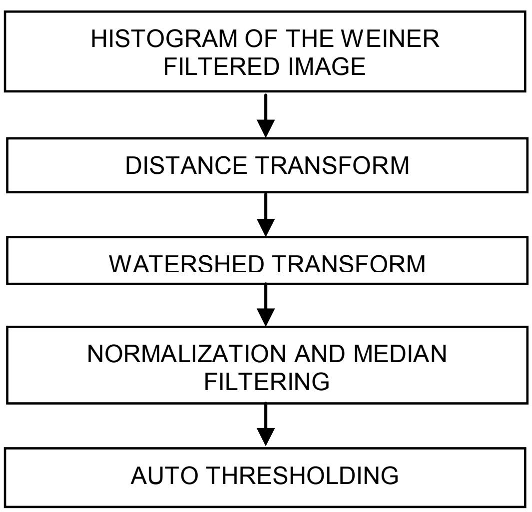

Figure 5. Auto thresholding.

fundamental importance in medical and biological coronary angiogram image.

(ii) Image enhancement

Next take histogram of the Weiner filtered wavelet transformed coronary angiogram image and perform histogram equalization technique as shown in Figure 4. The following conditions are set to perform histogram equalization:

For pixels <= 100, equalized to 50
For pixels <= 170, equalized to 128
For pixels <= 220, equalized to 190
Else, 230

(iii) Image segmentation

Image segmentation is done after image enhancement followed by applying watershed transform and auto thresholding. The detailed algorithm implemented is shown in Figure 5.

Auto thresholding algorithm

Step 1: Histogram is performed to determine the threshold value in order to segregate the coronary angiogram blood vessel from the background.
Step 2: Obtain the texture colored image.
Step 3: Compute the true Euclidean distance transform of the binary image. The distance transform assigns a number to each pixel of the given image which is the distance between that pixel and the nearest non-zero pixel of the given image.

The Euclidean distance (Qing et al., 2004) between two pixels (x_1, y1) and (x_2, y2) is defined as in Equation (1),

$$d_{euclidean}(x,y)=\sqrt{(x_1-x_2)^2+(y_1-y_2)^2} \qquad (1)$$

Step 4: Next compute the distance transform of the complement of the binary image.
Step 5: Compute the distance transform and force the pixels which do not belong to the edges to be at infinity.
Step 6: Compute the watershed transform and display the resulting label matrix as an RGB image.

Assuming that the image f is an element of the space C(D) of a connected domain D, then the topographical distance between points x and y is given as in Equation (2),

$$T_f(x,y)=\inf_{\gamma}\int\left|\nabla f(\gamma(s))\right|ds \qquad (2)$$

Where, '$\inf_\gamma$' is the overall paths inside D. Thus, let f ε C(D) have a minima $\{m_k\}_{k\varepsilon I}$, for some index set I. The catchment basin CB(m_i) of a minimum m_i is defined as the set of points C ε D, which are topographically closer to m_i than to any other regional minimum m_j and is given by Equation (3).

$$CB(m_i)=\{x\varepsilon D \mid \forall_j \varepsilon I\setminus\{i\}: f(m_i)+T_f(x,m_i)<f(m_j)+T_f(x,m_j)\} \qquad (3)$$

Thus, the watershed (Javadevappa et al., 2009) is the set of points which do not belong to any of the catchment basin as shown in Equation (4);

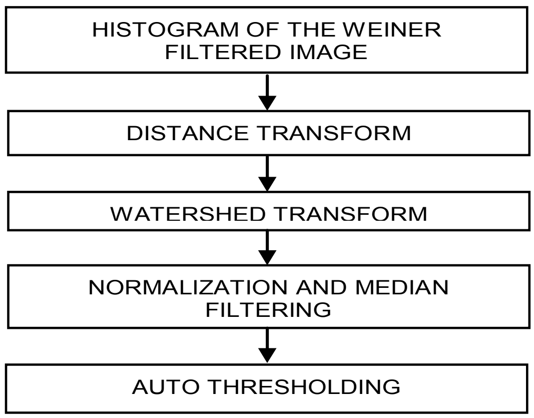

Figure 5. Auto thresholding.

$$W_{shed}(f) = D \cap \left(\bigcup_{i \varepsilon I} cB(m_i) \right) \quad (4)$$

Step 7: Perform normalization and median filtering. Preform image subtraction to eliminate the background of the given image. This is done by subtracting each element in the array y from the corresponding element in an array x of the given array(x,y) and then the difference between them is returned to the output array z.
Step 8: Perform intensity adjustment. This performs a mapping between the input image and output image based on intensity. Intensity values below Lin are mapped to Lout, intensity values above Hin are mapped to Hout, and values between Lin and Hin are mapped to values between Lout and Hout.
Step 9: Finally, auto thresholding is performed using the ISODATA method.

ISODATA method is used to perform auto thresholding which uses iterative technique. In this method, a global threshold is computed which is used to convert the intensity image to a binary image and is a normalized intensity value that lies in the range [0, 1]. This iterative technique was developed by Ridler and Calvard (1978). The histogram is initially segmented into two parts using a starting threshold value such as zero equal to half the maximum dynamic range. The sample mean (mf, 0) of the gray values associated with the foreground pixels and the sample mean (mb, 0) of the gray values associated with the background pixels are computed. Thus, a new threshold value 1 is now computed as the average of these two sample means. This process is repeated based upon the new threshold until the threshold value does not change any more.

Isodata algorithm

Step 1: Compute the mean intensity of the given image from the histogram H.
Step 2: Compute the Mean above H (MAH) and Mean below H (MBH) using H from step 1.
Step 3: New H = [MAH+MBH]/2
Repeat step 2 if H(i) ≈ H(i-1), Normalize the threshold to the range [i,1]
Level = (Th-1)/(n(end-1))

Morphological operations

Finally morphological operations are performed to segment the detected edges of the coronary angiogram image. First remove the interior pixels by setting a pixel to '0', if all its 4-connected neighbours are 1, thus leaving only the boundary pixels ON. Then remove the isolated pixels such as the individual 1's surrounded by 0's and also remove the H-connected pixels as these do not contribute to the edges of the coronary angiogram blood vessel. Generally a median filter is employed when the goal is to simultaneously reduce noise and preserve edges. Here each output pixel contains the median value in the m by n neighbourhood around the corresponding pixel in the input image. Thus, the blood vessels of the given coronary angiogram image is segmented using the integrated method of Discrete Wavelet transform and Watershed Transform (DWWSHD) along with the morphological operations.

(iv) Feature extraction

After segmentation feature extraction is done. From the segmented coronary angiogram image, features such as area, mean, standard deviation, variance, brightness, diameter, smoothness, compactness, skewness, kurtosis, eccentricity and circularity are extracted to train the neural network

(v) Classification of CAD using BPN

The classification of CAD using neural network basically consists of the following steps:

Step 1: Extracted feature transformation
Step 2: Network architecture definition
Step 3: Learning algorithm
Step 4: Validation

In the first step, the extracted features of section D are given to the neural network for recognition of particular patterns. In the second step, the number of neurons in each layer, and the number of hidden layers are defined. Also, the connectivity between each layer is defined. Usually, the number of input neurons, hidden neurons and output neurons depends on the problem studied. The network may not have required degrees of freedom to learn the process correctly, if the numbers of hidden neurons are small and vice versa.

In the third step, a leaning algorithm is used to train the network to respond correctly to a given set of inputs. Normally, the neural network is said to be well trained when there are more input data's available. It is possible to determine the weights through training, in which initially the weights are assigned to be random or based on experience. Thus, in the process of the learning algorithm, the network is said to change the weights systematically in order to perform the desired input output relation properly. In the fourth step, the validation is done in order to evaluate the performance of the system trained. The back propagation algorithm is given as below for the classification of the type of coronary artery disease.

Step 1: Read the number of layers and number of nodes in each layer
Step 2: Initialize the weights
Step 3: Read the pattern
Step 4: Calculate the number of output nodes in each successive layer
Step 5: Calculate the mean square error for a pattern
Step 6: Calculate the momentum of a node in the output node
Step 7: Update the weights between layers
Step 8: If the weights are not updated for all the layers, then calculate the momentum of a node in the hidden layer and repeat step 7
Step 9: Then calculate the mean square error for all the patterns

Table 1. Confusion matrix of the back propagation neural network.

S/No	Desired output	Classified normal	Classified abnormal
1	Normal	30	3
2	Abnormal	2	15

Table 2. Percentage of Correctness for the back propagation neural network.

S/No	Desired output	Classified normal	Classified abnormal
1	Normal	93.75	16.67
2	Abnormal	6.25	83.33

Step 10: If not go to step 3

The learning algorithm depends on three main parameters, namely, the learning rate, momentum, and the mean square error. The learning rate usually determines the change in the size of the weight, while momentum causes the weight changes to be dependent on more than one input pattern. Mean square error is the value at which the network error dips below a particular error threshold.

The two types of the CAD diseases are defined as Type 1 and 2 diseases. Type 1 disease is called eccentricity, in which the atherosclerotic plaque is not distributed along the entire circumference, leaving a variable arc of disease free wall. Type 2 disease is called concentric, in which the atherosclerotic plaque is distributed along the entire circumference of the internal elastic membrane.

EXPERIMENTAL RESULTS

The proposed algorithm was tested on the images acquired from 50 patients. The proposed algorithm was implemented and tested in MATLAB 7.0 on a Pentium IV Personal Computer (with Central Processing Unit 2.8G and 512 memory). The performance of the automated classification of CAD using back propagation network is evaluated using the following parameters:

(a) Confusion matrix
(b) Learning rate
(c) Hidden units

Testing of the back propagation neural network is done after the training phase. The data that are not trained by the netwrok, is applied to the neural network to evaluate its performance. Table 1 shows the confusion matrix for the result classification between normal and abnormal for this neural network. It is observed that two normal samples are classified incorrectly by the neural network as the subjects do not have either Type 1 or 2 coronary artery disease. Also, three abnormal samples are incorrectly classified as normal although the subjects do have coroanry artery disease. The confusion matrix can also be expressed as percentage of correctness as shown in Table 2.

From Table 2, it could is observed that the according to the percentage of correctness, the normal samples are classified correctly by the neural network with 93.75% of correctness and incorrectness by 6.26%. Persons who are having coronary artery disease are correctly classified with 83.33% while incorrectly classified with 16.67%. Thus, accuracy of classifying normal persons and abnormal persons are 93.75 and 83.33%. The performance of the back propagation neural network for various learning rates ranging between 0.1 to 1.0 is observed as shown in Table 3. The training is done with 50 coronary angiogram images. From Table 3, it is observed that the average training time ranges from 2.36 to 1.98 s and the average testing time ranges from 0.0142 to 0.0088 s for the learning rate varying from 0.1 to 1.0 in steps of 0.1. Also, the Type 1 classification efficiency is 90% and Type 2 classification efficiency is 92% at a learning rate of 0.7 which is said to be the optimum learning rate. The corresponding average traininng time is 2.18 s and average testing time is 0.0105 s.

From Table 4, it is observed that the objective of the network is not met upto hidden units of 30, beyond which it is achieved. The maximum classification efficiency for Type 1 and type 2 are 85 and 89% at 50 hidden units with an average training time of 1.93 s and average testing time of 0.0156 s. Thus, the application is said to have one hidden layer with fifty hidden units. From Table 5 it can be seen that the accuracy of classifying the CAD using DWWT and BPN automatically by the proposed method is 89%, which is predominant as compared to the other methods specified in the literature.

SIMULATED RESULTS

The simulated results are shown in Figures 6 to 7 for both the proposed automated classification of CAD using BPN. Only two input images and its superimposed output coronary angiogram images along with its classification of CAD type are shown for simplicity. Figure 6 shows the input coronary angiogram image which is tested for the Type 1 CAD. Figure 7 shows the region properties

Table 3. Average training time, average testing time and classification effeiciency for different learning rate.

S/No	Learning rate	Average training time (s)	Average testing time (s)	Classification efficiency (%)	
				Type 1	Type 2
1	0.1	2.36	0.0142	84	82
2	0.2	2.33	0.0138	79	80
3	0.3	2.30	0.0138	82	80
4	0.4	2.29	0.0125	85	87
5	0.5	2.23	0.0117	80	82
6	0.6	2.20	0.0116	82	83
7	**0.7**	**2.18**	**0.0105**	**90**	**92**
8	0.8	2.14	0.0103	82	84
9	0.9	2.11	0.0098	77	78
10	1.0	1.98	0.0088	75	76

Table 4. Average training time, average testing time and classification effeiciency for different hidden units.

S/No	No. of hidden units	Training status	Average training time (s)	Average testing time (s)	Classification efficiency (%)	
					Type 1	Type 2
1	5	Not met	-	-	-	-
2	10	Not met	-	-	-	-
3	15	Not met	-	-	-	-
4	20	Not met	-	-	-	-
5	25	Not met	-	-	-	-
6	30	Not met	2.48	0.0192	65	68
7	35	met	2.22	0.0184	69	68
8	40	met	2.18	0.0175	73	75
9	45	met	2.10	0.0166	77	78
10	**50**	**met**	**1.93**	**0.0156**	**85**	**89**

Table 5. Percentage of correctness for the back propagation neural network.

S/No	Methods	Accuracy (%)
1	Crisp rule based classifier (Markos et al., 2008)	58.3
2	Adaptive Neuro Fuzzy Inference system (Markos et al., 2008)	56.8
3	Optimized Fuzzy Model (Markos et al., 2008)	73.4
4	Artificial Neural Network Method (Markos et al., 2008)	73.9
5	Fuzzy Support decision system (Noor et al., 2009)	87
6	Proposed method	89

stages, Figures 8 and 9 shows the features extracted and the extracted blood vessel. Figure 10 shows the training of the neural network and Figure 11 shows the testing phase, while Figure 12 shows the superimposed image and classified Type 1 CAD by Figure 13. Figure 14 shows the input coronary angiogram image which is tested for the Type 2 CAD along with the extracted blood vessel. Figure 15 shows the training of the neural network and Figure 16 shows the superimposed image and classified Type 2 CAD by Figure 17.

Conclusion

It is concluded that the automated classification of coronary artery disease using the back propagation neural network has yielded a 93.75% normal classification and a 83.33% abnormal classification by integrating the discrete wavelet transform and watershed algorithm along with morphological operations. Also, Type 1 classification efficiency of 90% and Type 2 classification of 92% has been achieved at a learning rate

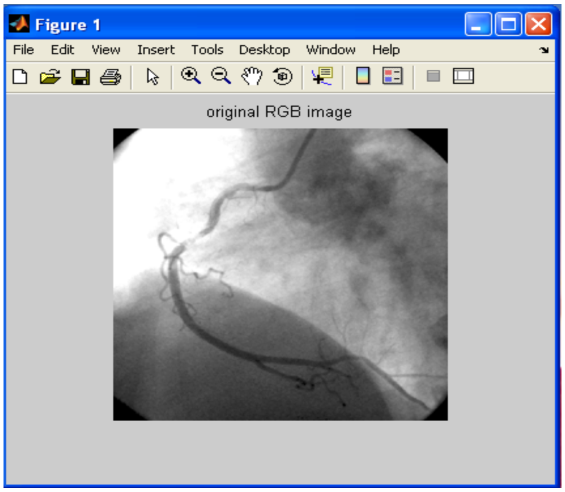

Figure 6. Input coronary angiogram image.

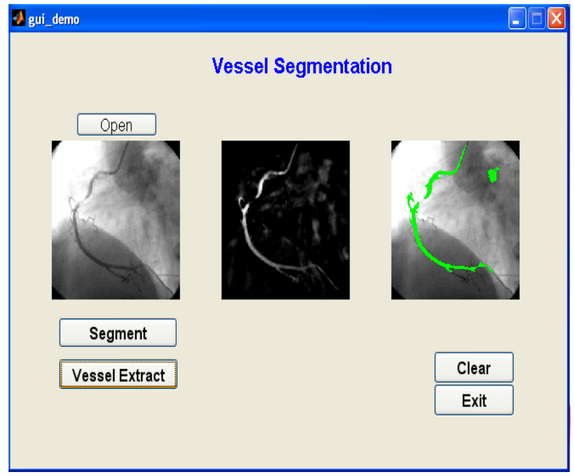

Figure 9. Extracted coronary angiogram of type 1 CAD.

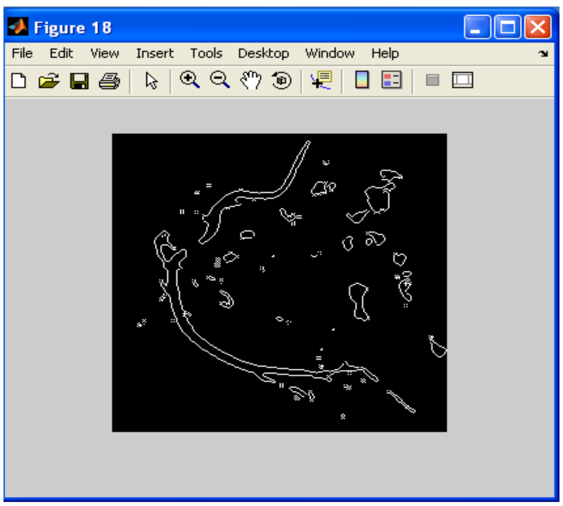

Figure 7. Region properties stages.

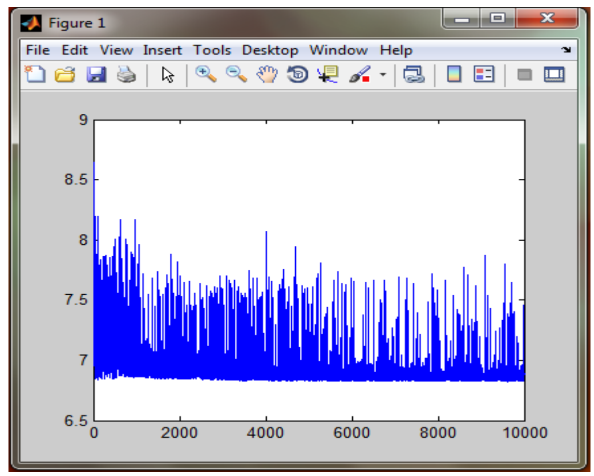

Figure 10. Training process for Type 1 CAD.

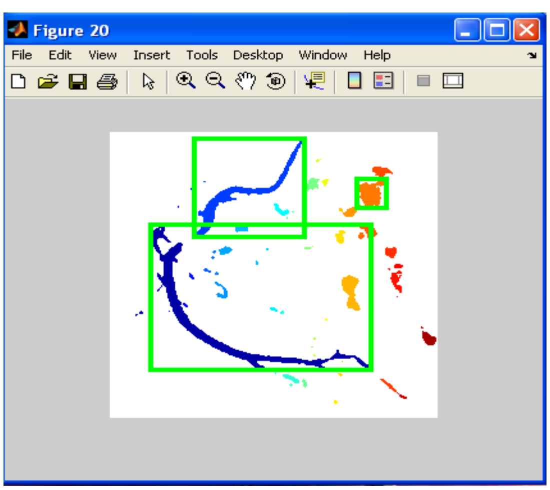

Figure 8. Feature extraction.

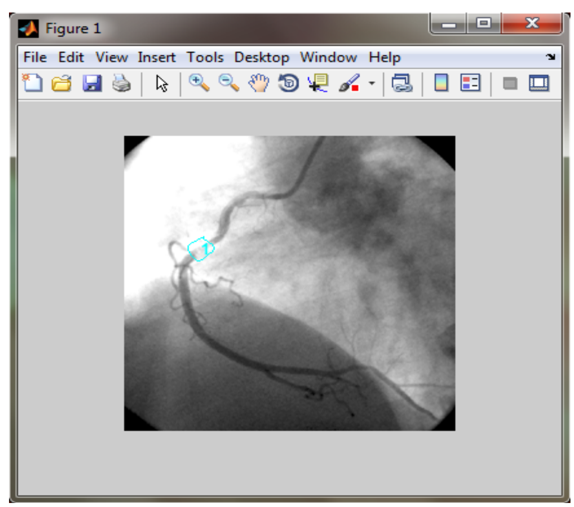

Figure 11. Testing process for Type 1 CAD.

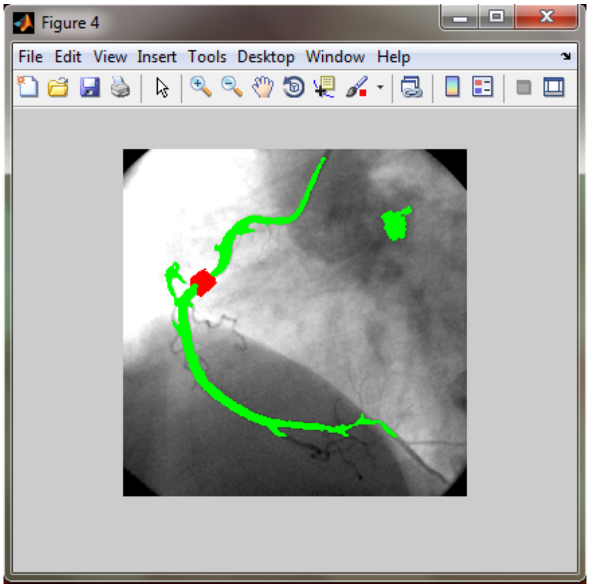

Figure 12. Superimposed image for Type 1 CAD.

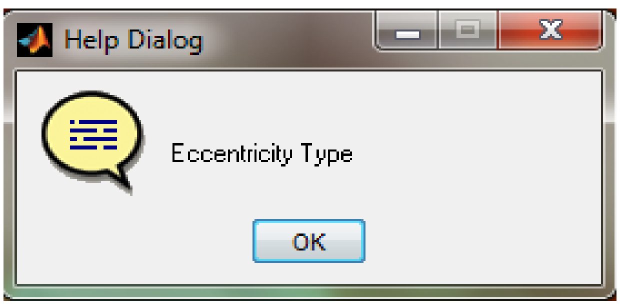

Figure 13. Type 1 CAD classified.

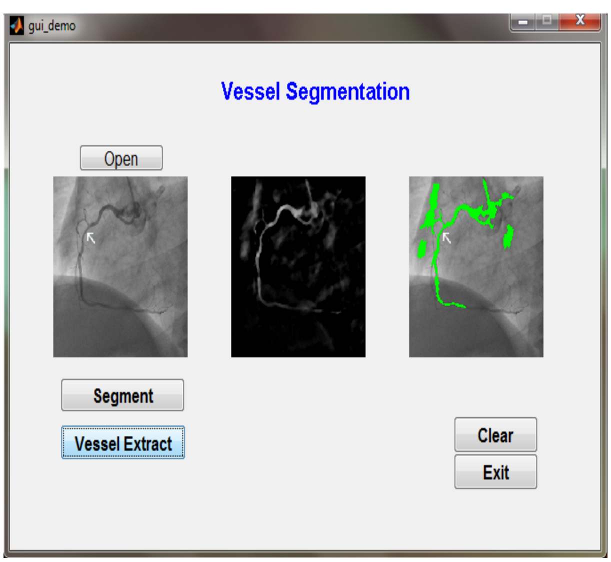

Figure 14. Extracted coronary angiogram of type 2 CAD.

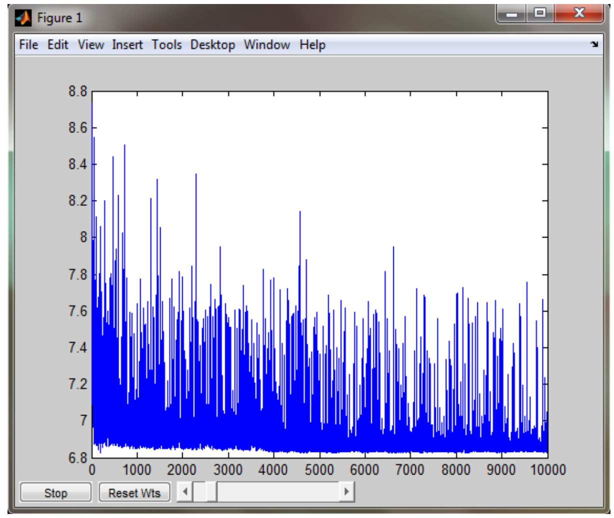

Figure 15. Training process for type 2 CAD.

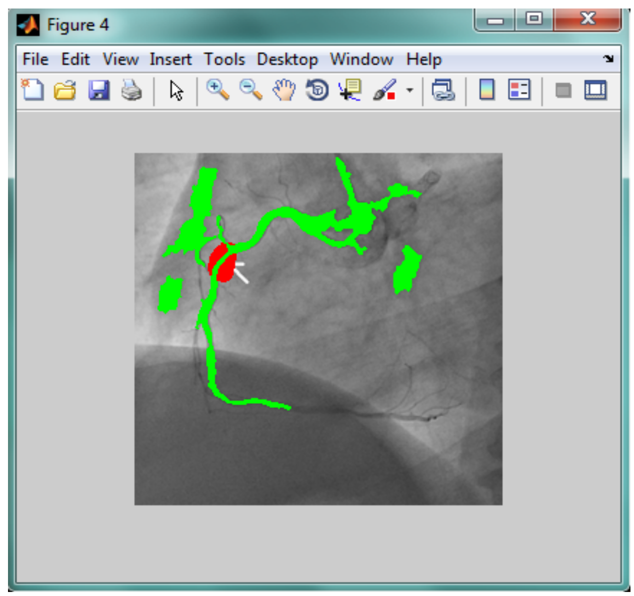

Figure 16. Superimposed image for type 2 CAD.

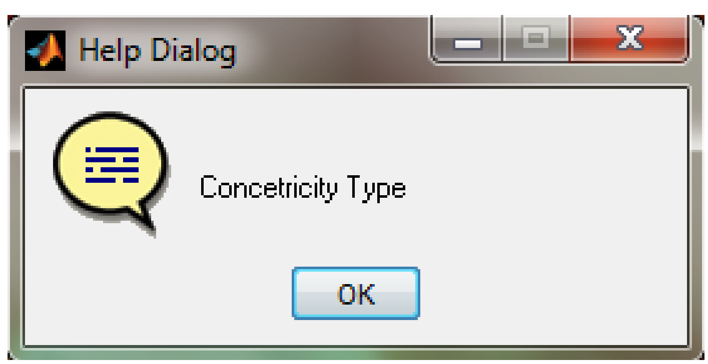

Figure 17. Type 2 CAD classified.

of 0.7 and Type 1 classification efficiency of 85% and Type 2 classification of 89% has been achieved for 50 hidden units of the neural network. An accuracy of 89% in classifying the CAD using DWWT and BPN automatically is achieved, which is predominant as compared to the other methods specified in the literature.

Conflict of Interests

The author(s) have not declared any conflict of interests.

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