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Computer Assisted System For Classification Of Wall Thickness In Ultrasound Carotid Artery Images Using Neural Networks

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Abstract:
The aim is to classify the carotid artery ultrasound images. This is done by developing a system i.e. a decision making system for automated diagnosis of the ultrasound images. The system proposed classifies the images into normal ,cardiovascular and cerebovascular diseases. The ultrasound images are preprocessed and then for each image two contours are extracted. Inorder to classify the images the multilayer back propogation network system has been developed. The system along with the contour extraction algorithms works efficiently and results shows that this system provides an higher level of classification of the ultrasound images with reduced time.

1.Introduction

Advancements in the medical imaging techiniques have, without doubt, led to easier and more accurate diagnosis of pathologies. But the accurate extraction and differentiation of various minute anatomical features still requires improvement. Manual interpretations are prone to be inaccurate because of the noise that may be present in the image. To simplify this process and to make it more efficient, a number of automated methods have been proposed already for this purpose, predominantly using Computer-Aided Diagnosis(CAD)[2].The identification of these features helps the physicians diagnose the ailment.

Recently several CAD techniques have been proposed for the diagnosis of various organs. Huozhimin et al. proposed an automated method to distinguish benign tumors from malignant tumors by analyzing the lesion density. A more novel approach for the same was proposed by Aoyoma et al.[1] In their work a parameters such as age, sex and other features were extracted using linear discriminant analysis. The cluster of features so obtained was fed in to an Artificial Neural Network(ANN). The results obtained using this method were more accurate.

Ashizawa et al. proposed a technique to distinguish between 11 interstitial lung diseases using ten clinical parameters and 16 clinical findings. Using ANN differential diagnosis of lung diseases can be made by analyzing chest radiography[3]. Verikas et al. proposed a technique for automated analysis of vocal cord diseases using CAD[7]. Colour , texture and other geometrical features were used to obtain a clear image of the vocal tract. Jerebko et al. proposed a method of diagnosing colonic polyps using CAD technique. Neural networks and binary trees were compared to classification results to decide the best classifier.[9]

The above procedures have showed that neural networks can provide more accurate results concerning feature didtinguishing. The different features that are obtained using different methods are fed into the neural network system and the results so obtained are found to be very reliable. In our carotid artery classifier systemsystem, Multilayer Back Propagation Network(MBPN) to classify CCA into three categories namelynormal(NR),cardiovascular diseases(CVD),and cerebrovascular diseases(CeVD).[4-6]

2.Methods

The method used for the classification of the ultrasound carotid artery images is by using the carotid artery classifier system. So for the carotid artery classifier system the input given is the images acquired by the ultrasound scanned images. The carotid artery classifier system can be segmented into three areas basically for detecting the abnormality in the carotid artery :

- Generalprocessing
- Preprocessing
- Analysis

The general processing methods includes the image acquisition ,digitization and verification of the images to see whether the images are correct or reacquisition is required.

The preprocessing algorithms is used for the segmentation of the structures and here normalization of the images is done and then followed by speckle reduction and filtering,

The analysis section is the most important section where the problem solving is done like contour extraction, classification by the decision support systems(neural network based system)

3.Acquisition Of Images Using US Scanners

The ultrasound carotid artery images are obtained using different scanning systems , some them used in this work are :

- AlokaProsoundAlpha-10 (SSD α-10, model no.M00720Japan)
- PhilipsHD11XEUSmachine(modelno.—HDI5000 sonoct)

The normal and abnormal subjects are tested and the ultrasound images of their carotid artery are obtained . The transducer is moved around at different inclined angles for both the subjects to get a better visualization of the carotid artery, both the transerve and longitudinal sections of the carotid artery. The video is recorded for a time period of 10s or 15s to get a view of the transverse and longitudinal sections of the carotid artery for both the normal and abnormal subjects. Using video decompiler he videos obtained is converted into frames. Then these frames are stored as still images and then for further processing are fed into the computing systems. Thus the carotid artery images for the normal and abnormal subjects are obtained for analysis .

4.Carotid Artery Diseases

This disease causes the rupture and malfunction of the blood vessels that deliver blood to the brain. This disease is caused because the artery gets blocked or becomes narrower due to the build up of a waxy substance called plague. The carotid Arteries that supply blood to the brain split up into to sections on delivers blood to the brain while the other delivers blood to the frontal part of thehead.Atherosclerosis is the hardening of the arteries in the interior of the vessels. This reduces the flow of oxygen rich blood to the brain causing reduced brain functions. The arteries become hard and loose their elastic properties and become hard. This decreased blood flow causes the blood pressure to increase. Carotid Artery Diseases may occurdude to genetics and tobacco smoking. The increased thickness can be measured using an ultrasound and an Edge detection software to measure the amount of disease present.

5. Preprocessing And Contour Extraction For Carotid Artery Of US Carotid Artery Image

The carotid artery region is reserved from the surrounding tissue, the following steps are followed

- Separate the required region
- The intensity is normalized using average intensity histogram
- Echo dropouts are removed using Horizontal smooth flickering
- Vessel interfaces are located

The improved dynamic programming Algorithm is used to extract the Arterial layers. Optimization principle is used to detect the boundaries.

The speckle reducing anisotropic diffusion technique is used in active contour extraction. After this the energy minimization process is used for contour extraction.

6. Neural Network Classifier Implementation

Neural network plays a very important role in this study. Here in the implementation there are four basic steps:

- Data Scaling And Normalization

Here in this step due to the huge variations in the data values the network works slowly. So to prevent such a condition the data is either scaled or normalized to a smaller value (between 0 to 1). The normalization is given by :

Input data = original date / normalization factor

In this study the input data is the arterial thickness so:

Original data = arterial thickness value

Normalization factor = maximum value if the arterial thickness.

- Network Architecture Definition

There are three levels of data processing units- input, hidden and output layers. There are processing neurons in each layer. Depending on the problem , the number of input , hidden and output neurons are chosen. The number of hidden layer neurons must be optimum. This is because, very less number of neurons will lead to insufficient degrees of freedom and very high number of neurons will cause the training to take a long time and result in over fitting of data. To determine the optimum number of neurons, validation set error is used. Thus basically, the number of hidden layers, the number of neurons in each layer and the connectivity between each layer is set in this layer.

- Learning Algorithm

In the third step, the network is trained using a learning algorithm. The network must resond to a set of inputs correctly. The goal of this training is to find the parameters for which the performance is maximum. Better training of ANN is achieved using more inputs. Training is aimed at determining the weights. For this the weights are initialized with random values at the beginning of the exercise. The training process is complete when the difference between actual ANN and obtained output is very small.Several training methods are available for training the ANN.

- Validation Step

Finally, the trained ANN is tested for performance using some validation set data. Validation can be used to find the optimum number of training iterations and the optimum number of hidden neurons.

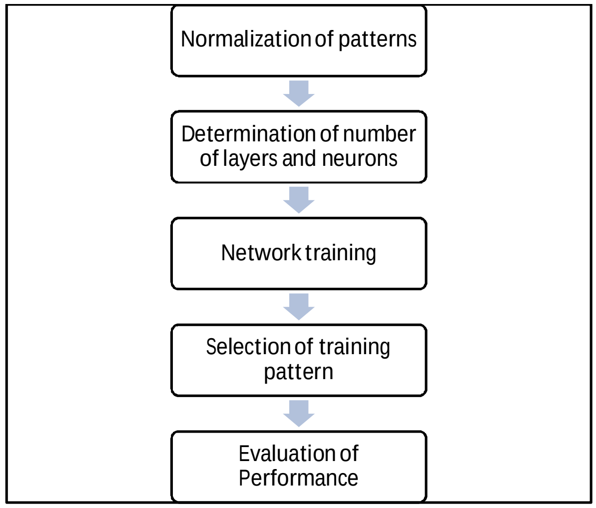

Figure 1: Steps involved in Algorithm

6.1. MBPN

This is a method to train networks. Used to train networks in several domains such as speech and character recognition. The architecture is a network of nodes in layers.

There are three or more layers, they are as follows,

An input layer which is used to measure the external inputs, an output layer to display the outputs and a set of hidden layers. There is no computation involved in the input layer. When an input is received at the input layer the middle layers perform calculations on the data and the result is presented at the output layer.

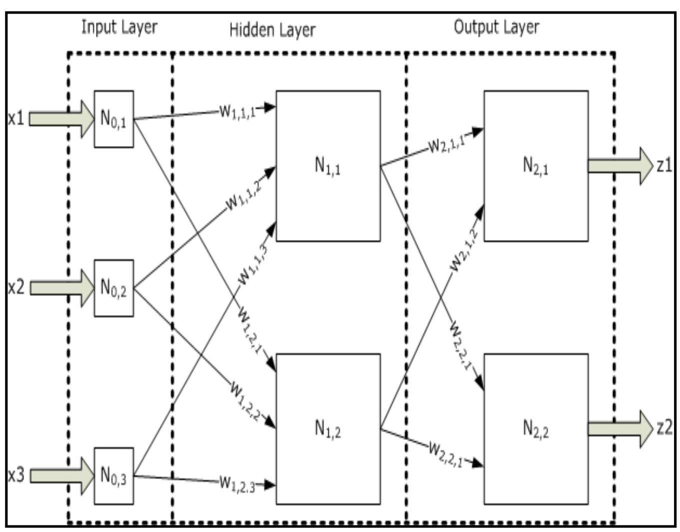

Figure 2: BPN neural classifier

6.1.1. Training

Training requires a series of known and verified network behaviors and characteristic of the input and output nodes. The weights and biases are changed and the performance is measured and quantized as the Mean square Error.

Training involves the following processes,

- The data is preprocessed before the training process.
- The weights are initialized
- For an input sample the outputs of both output and hidden layer is calculated
- Errors are calculated
- Weight values are adjusted according to error function

Training process are mainly dependent on 3 parameters

- learning coefficient (η),
- momentum (β), and mean
- square error (δmax)

6.2 Back Propagation Algorithm

This algorithm considers steepest decent method for analyzing global minimum and supervised method for determining the minimum error value.

The number of layers and the number of nodes in the input, output and hidden layer are determined. The number of processing nodes in the input layer depends on the problem and the number of inputs. The classification nodes in the output layer are also chosen based on the problem. Random weights are assigned to the connections between nodes.

In the input layer, a training set pattern is fed and the errors are analysed in the output layer. The weights are updated by propagating the error in the backward direction. This process is done repeatedly. After each iteration, the generated test patterns are fed to ANN and their performance evaluated. The iterations are continued until the desired classification performance is reached.

Algorithm

Step 1 : The input vector X is fed to the input of the system

Step 2 : Forward propagation

- The input and output of the pattern are fed to the network after initializing the weights and thresholds.
- Net input of jth hidden node is given by,

- net j= i=1N$W_{ij}X_i + \theta_j$
- Output of each node in the jth hidden layer is given by,

  Ohidden layer= 11+exp (net j)

  $O_{j = 11+\exp}$ (i=1N$W_{ij}X_i + \theta_j$)
- This value is propagated to the kth output layer . The net input values at kth layer is given by,

$$\text{net } k = \sum_{j=1}^{L} W_{kj}O_j + \theta_k$$

  W- weights , O- outputs biased term for hidden nodes
- The output of each node in the utput layer is given by,

$$O(\text{outputofanode}) = \frac{1}{1 + \exp(\text{net}k)} \; O_k = \frac{1}{1 + \exp\left(\sum_{j=1}^{L} W_{kj}O_j + \theta_k\right)}$$

- E(p) represents the error of an output pattern is calculated as

$$\delta(\text{hidden layer}) = E(p) = \left(\frac{1}{2}\right)\sum\left(d(p) - O_j(p)\right)^2$$

Step 3: Backward Propagation

- The error for the outputs is calculated and is given by

$$\delta(\text{hidden layer}) = E(p) = \left(\frac{1}{2}\right)\sum\left(Y(p) - O_k(p)\right)^2$$

  Y(p) – Target output

  $O_k(p)$ – actual output from the kth output node
- The weights between output layer and hidden layer is calculated using the formula,

$$W(n+1) = W(n) + \eta\delta(\text{outputlayer})O(\text{hiddenlayer})$$

- The error for hidden nodes is given by,

$$\delta(\text{hiddenlayer}) = O_k(p)(1 - O_k(p))\sum\delta(\text{output layer})$$

- The weights between output and hidden layers are calculated as follows,

$$W(n+1) = W(n) + \eta\delta(\text{hiddenlayer})O(\text{inputlayer})$$

These steps complete one update of weight. The same is repeated for the second pattern to obtain a second weight update. After all the training patterns are presented, one iteration cycle is completed.

Error of training patterns in terms of MSE is given by

$$E(MSE) = \sum E(p)$$

7.Result

The study of the architectural issues of the network have led to the construction of the multilayer back propogation network carotid artery classifier system. Now using this system the ultrasound carotid arteries of the normal and abnormal subjects are tested and then categorized. These results tell us that the system is reliable and also efficient.

Now based on the inouts given the classification is done. The system's output is normal if the thickness of the carotid artery is less than 1mm. If the thickness is more than 1mm due to some pathologies then the output for those subjects is abnormal and those subjects have to meet the doctors for further treatment. Thus,in this work the study of both the normal and abnormal subjects have been analysed.

8.Conclusion

Thus the classification of the ultrasound carotid artery images is done to fall in the basic three categories mentioned. This is successfully achieved by developing and implementing the multilayer back propogation network based carotid artery classifier system. The characteristics or important features of the carotid artery images are retained in order to extract the contours of the different layers of the carotid arteries. This work emphasizes on the fact that the multilayer back propogation network based carotid artery classifier system offers higher classification and more accuracy and efficiency. As the input images are actually classified based on some values it is possible to create a universal reference for the different categories discussed and then make a comparative study to come upon the classification and the amount of pathology. It is also possible for the doctors to use the proposed method to determine whether a normal patient with a normal carotid artery will become abnormal or not based on the intima media thickness value. This proposed method has a lot of clinical applications as it helps the doctors in the classification of the carotid arteries.

9.Reference

1. Aoyama M, Li Q, KatsuragawaS, MacMahonH, DoiK: Automatedcomputerizedschemefor distinctionbetweenbenign and malignantsolitarypulmonary nodulesonchestimages.MedPhys29(5):701–708,2002
2. Summers RM: Road maps for advancement of radiologiccomputer-aideddetectioninthe21stcentury.Radiology229:11–13,2003
3. NishikawaRM, GigerML, Doi K, VybornyCJ, SchmidtA: Computer-aided detection of clustered microcalcificationsondigitalmammograms.MedBiolEngComput33:174–178,1995
4. .LoizouCP, Christodoulou C, PattischisCS, etal: Speckle reductioninultrasoundimagesof atheroscleroticcarotidplaque. IEEE Proc. Santorini, Greece:14th Intl. Conf.DigitalSignal Processing,2002,1:525–528
5. GletsosM,MougiakakouSG,MatsopoulosGK,NikitaKS,NikitaAS,KelekisD:Acomputer-aideddiagnosticsystemto characterizeC Tfocalliver lesions:designandoptimizationofaneuralnetwork classifier. IEEE TransInf Technol Biomed7(3):153–162,2003
6. Schmid-SaugeonP,GuillodJ,ThiranJ-P:Towardsa computer-aideddiagnosissystemforpigmentedskinlesions.ComputMedImaging Graph27:65–78,2003
7. VerikasA, GelzinisA, BacauskieneM, UlozaV: Towards a computeraideddiagnosissystemforvocalcorddiseases.ArtifIntellMed36:71–84,2006
8. Yoshida H, DachmanAH: CAD techniques, challenges and controversiesinCTcolonography.J AbdomImaging30:24–39,2005
9. JerebkoAK,SummersRM,MalleyJD,FranaszekM,Johnson CD: Computer-assisteddetection of colonic polyps with CT colonographyusing neural networks and binary classification trees.MedPhys30:52–60,2003