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A Review and Comparative Study of Methods used in Finding Carotid Artery Abnormalities using Ultrasound Images

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Abstract : Atherosclerosis is solidifying of veins because of hypertension and elevated cholesterol. It causes stroke, heart attack, stenosis and many other conditions which may lead to death. In ultrasound, no inquiry of radiation, but speckle noise which is produced because of the small particles in the tissues, with size less than the wavelength of the ultrasound is the issue which has to be addressed. In this paper we are evaluating and comparing the different methods in finding the intima- media thickness (IMT), lumen thickness, adventitia boundary and the plaque diameter on B mode ultrasound images. The paper starts with an audit of clinical strategies for visual characterization that have prompted institutionalized techniques for denoising, image segmentation, classification, and gives a review of the few feature extraction and other strategies that have been connected. Finally emerging trends and future perspectives are viewed in a comprehensive way.

Keyword : Speckle noise, image gradient, active contour, texture

1. INTRODUCTION

Exact, reliable, effective, and exact estimations of the geometry of the normal carotid artery (CCA) are vital for evaluating and dealing with the advancement of carotid atherosclerosis and also surveying the danger of stroke. Abnormalities in Intima media thickness (IMT) is the main indicator of stroke. Medicinal ultrasound imaging has been utilized for viable diagnostics of illnesses over the previous decades because of its noninvasive, safe, compact, precise and financially savvy qualities. In this manner, if persistent subgroups with adequately higher than normal danger, regardless of ideal medical intervention, could be reliably distinguished, then carotid surgery could be performed in those that are liable to advantage[1].

Carotid intima-media-thickness (IMT) is an estimation of the thickness of the deepest two layers of the blood vessel divider and gives the separation between the lumen-intima and the media-adventitia thickness. Contrasted with MRI and CT, ultrasound has a few focal points: it is protected, non-invasive and economical. Concerning ultrasound imaging, it gives geometry, as well as stream data, for example, speed and volumetric stream rate in the same area of the vessel. In spite of the fact that in ultrasound imaging, diverse segmentation strategies were produced for IMT , no strategy was created for the segmentation of the atherosclerotic carotid plaque in longitudinal ultrasound pictures. A lot of examination has concentrated on the evacuation of speckle noise.

The paper is organized as follows. Section II portrays the filters in point of interest for preprocessing of carotid artery ultrasound. Section III gives a summarized review of Segmentation and Normalization algorithms in the carotid artery application used so far. Section IV summarizes the Feature extraction and Optimization techniques involved in detecting CCA abnormalities. Section V deals with classifying the image as normal or abnormal based on the parametric values. Section VI concludes the paper.

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2. PREPROCESSING

The multiplicative speckle noise corrupts the visual assessment in ultrasound imaging by reducing image intensity and contrast. Quick, versatile, modest and capable of real time imaging, yet shockingly, be that as it may, precise ultrasound pictures, need valuable conclusions from the pictures because of noise degradation's. The objective of a image denoising technique is to recuperate the spotless picture from its noisy version by evacuating noise and holding however much as could reasonably be expected the useful information.

Kaun filter gives superior results than average and bilateral filtering techniques. Here, the multiplicative noise model is initially changed into signal dependent additive noise model. Then minimum mean square error criteria is applied. Gabor filter is a type of wavelet. Geometrical filter has lower speckle reduction capability but assures minimum computational complexity. The execution of homogeneous filter, demonstrated a change of 3% in texture analysis, in picture quality measurements geometric filter does not deliver productive results and as indicated by the visual assessment by specialists the homogeneous filter gave 45% average score and 68% average score via cardiovascular and neurovascular specialist separately. Weiner filter showed modifications in GLDS and NGTDM feature set. Image blur and low contrast images are obtained which is the problem with this technique [2]. Bilateral filtering removes both low and high frequency noise[3]. Combining bilateral filtering with LDA technique has better performance in means of PSNR. Some speckle noise specific denoising techniques are discussed here.

A. Wavelet Transform

Wavelet denoising endeavors to evacuate the noise present in the signal while saving the signal qualities for any frequency component. Since Discrete Wavelet Transform subjects to basis decomposition, it provides non redundant and unique way of representation. Multiresolution, sparsity, edge detection, and edge clustering properties of wavelet transform makes it more suitable for denoising. The method of wavelet decomposition comprises of back to back operations on rows and columns of the two-dimensional information. The wavelet transform first performs one stage of the change on all rows. This procedure yields a matrix where the left side contains down examined low pass coefficients of every row, and the right side contains the high pass coefficients. Next, one stage of decomposition is done to all columns ; this outcomes four sorts of coefficients, HH, HL, LH and LL[4].

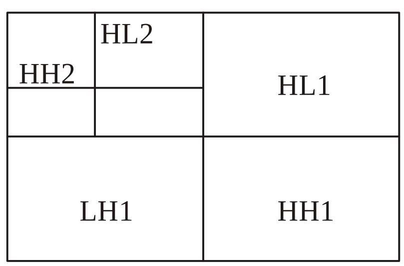

Fig. 1. Two Level Image decomposition by using DWT

Hard-thresholding is described as

$$\eta 1(w) = wI((|w| > T) \quad (1)$$

Where w is a wavelet coefficient, T is the threshold. The soft-thresholding function is described as

$$\eta 2(w) = (w - \mathrm{sgn}\,(w)\,T)\,I\,(|w| > T) \quad (2)$$

Where sgn (x) is the sign function of x. The soft-thresholding rule is chosen over hard-thresholding[4]. As a rule a little threshold value will abandon all the unwanted noise coefficients and in this manner the resultant denoised picture might in any case being little more noisy. Then again a large threshold makes more number of coefficients as zero which coordinates to smooth the signal decimates subtle elements and the resultant picture might bring about artifacts. So ideal edge quality ought to be discovered, which is versatile to various sub band attributes. Global thresholding may also be performed, where thresholding in diagonal band alone is performed and applied to horizontal, vertical and sub bands. In terms of PSNR and visual quality, the wavelet shrinkage filter gives better results than adaptive speckle filters.

B. Anisotropic Diffusion Filter

Anisotropic diffusion is a nonlinear smoothing filter which utilizes a variable conductance term that controls the difference of the edges that thus impact the diffusion. The conduction coefficient is set as zero near the edges and one within the region, but estimating presence of edge is the difficult part. So the conduction coefficient can be chosen locally as a function of the magnitude of gradient of brightness function of image to get edge values[5]. The gradient boundary detects an image boundary as a step discontinuity in intensity. Anisotropic diffusion is given as below.

$$I(x,0) = I_0;\ \partial\ I/\partial t = \mathrm{div}(F) + \beta(I_0 - I) \tag{3}$$

where, I is the input image, I_0 is the initial image, F is the diffusion flux and β is a data attachment coefficient[5]. If $\beta = 0$, particular cases of equation are: The heat diffusion equation $F = \nabla I$ which is equivalent to Gaussian convolution. The non linear probability density function (PDF) with $F = c(|\nabla I|)$. ∇I where, ∇ is the gradient operator, div is the divergence operator, || denotes the magnitude diffusion coefficient $c(x)$ given by,

$$C(x) = \exp[-(x/k^2)] \tag{4}$$

In the diffusion coefficient function, both gray level variance and gradient can be incorporated to preserve image details in a better way.

C. Adaptive Filter

The algorithm first isolates a picture into its low pass and high pass filtered structure segments. The lows part then controls the amplitude of the highs segment to increase the local contrast. The lows part is then subjected to a non linearity to alter the nearby luminance mean of the picture and is consolidated with the handled highs part. This makes changes in local contrast and local luminescence mean. In figure, $f(n_1, n_2)$ denotes the unprocessed digital image and $f_L(n_1, n_2)$ denotes the local luminance mean of $f(n_1, n_2)$ is got by low pass filtering $f(n_1, n_2)$, The sequence $f_H(n_1, n_2)$ which denotes the local contrast is obtained by subtracting $f_L(n_1, n_2)$ from $f(n_1, n_2)$.

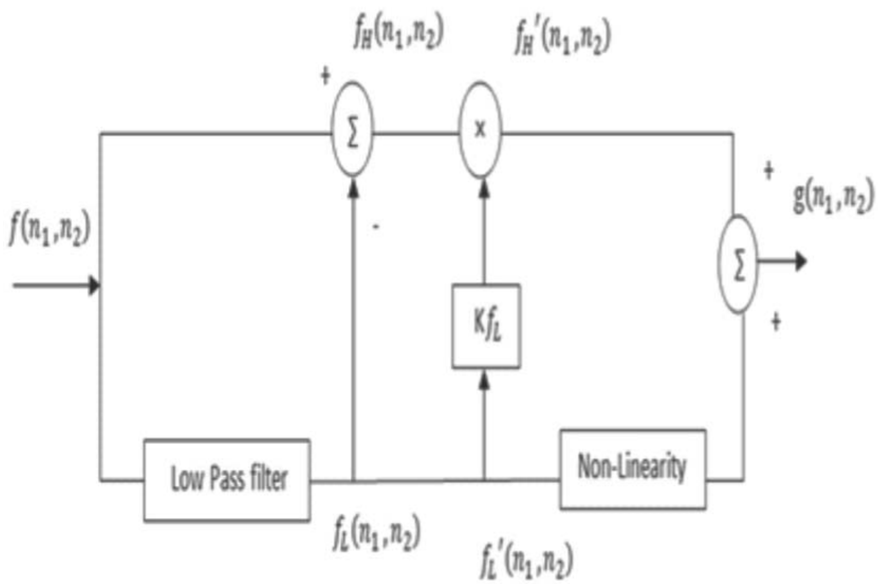

Fig. 1.Block Diagram of Adaptive Filter

The local contrast is modified by multi1pling $f_H(n_1, n_2)$ with $k(f_L)$, a scalar which is a function of $f_L(n_1, n_2)$. The modified contrast is denoted by $f_{HI}(n_1, n_2)$[6]. The function $f(k_L)$ is application specific, its value greater than 1 represents increase of local contrast and less than 1 represents decrease in local contrast.

3. SEGMENTATION AND NORMALIZATION

Developing methodologies in plaque ultrasound picture investigation incorporate the recent 3-D imaging strategies, plaque movement examination, stress and strain imaging, and the utilization of contrast agents. The difficulties are carotid artery has severe and unpredictable bends in its major axis. Various CCA segmentation methods have been proposed in the most recent couple of years either for the division of the intima–media complex (IMC), the lumen of the CCA, or for the atherosclerotic carotid plaque from ultrasound pictures or recordings of the CCA. The present audit study proposes and examines the techniques and frameworks presented so far for performing automated or semi-automatic segmentation in ultrasound pictures or recordings of the CCA. The Performance assessment for segmentation methods can be done by Hausdorff Distance, Polyline distance Metric, Percent static test, manual and computer measurements comparison and mean absolete distance.

A. Active Contour Model

Active contour or snakes, are bends characterized inside of a image area that can change position by inward powers originating from inside of the bend itself and outer powers registered from the picture information. The crucial thought is to advance a bend or a surface under limitations from picture drives so it is pulled in to required features for a picture. Snakes are broadly utilized as a part of applications like edge detection, shape demonstrating, segmentation, and tracking motion. Data inside the boundaries must also be considered to detect exact edges is active contour without edges[7].

$$\begin{aligned} E_{internal} &= E_{cont} + E_{curv} \\ E_{image} &= W_{line}\, E_{line} + W_{edge}\, E_{edge} + W_{term}\, E_{term} \end{aligned} \tag{5}$$

Where W are the weights of salient features. Higher weights have a larger contribution to image force (line or edge or termination). This model can include automatic image normalization. Level Set formulation is used in geometrical active contour model. Minimization of intrinsic weighted Euclidian length called geodesic active contour model was introduced. The basic thought is to begin with first boundary shapes spoke to in a sort of closed bends, contours, and iteratively transform them by applying shrink/development operations as indicated by the imperatives of the picture. The conjunction of edge and region based information sources by active contours was done to get better segmentation results[8]. Improved snake model wavelet vector flow (WVF) snake combines wavelet vector flow and gradient analysis[9]. The method is insensitive to noise in image and has the capability to segment complex medical images. With maximum deviation of 3.4 pixels (0.0248 mm) for IMT, CCA walls were segmented based on frequency implementation of active contours. It is a full automatic method to obtain initial contours.

B. RANSAC and cubic splines

Random Sample Consensus is an iterative method to estimate the parameters in a mathematical model from a set of obtained information in the image which has outliers. More the iterations, better is the probability of achieving accurate segmented results. 73% of Near and 95% of far end adventitia boundary of CCA in ultrasound images are semi automatically segmented in this method.[10] Zero order B spline functions gives worst results and third order interpolation provides best results. The Algorithm is as follows.

1. To identify the model parameters, the least number of points necessary are selected randomly.
2. The models coefficients are solved.
3. Find the number of points with a given tolerance.
4. We need to repeat the process if a portion of the inliers over the total points in the set surpasses a given value. Then end.
5. Else, repeat steps 1 through 4 (with a maximum of N times).

Set number of iterations N a high value so that at least 1 set of random sample excludes an outlier. Let u be the probability with a point in an inlier and $v = 1 - u$, the probability of identifying an outlier. N iterations of the minimum number of points denoted m are required, where

$$\begin{aligned} 1 - p &= (1 - u^m)^N, \text{ After necessary calculations,} \\ N &= \log(1 - p)/\log(1 - (1 - v)^m) \end{aligned} \tag{6}$$

C. Hough Transform

It detects LI interface boundary. The line with the most elevated value in accumulator array, which additionally satisfies the prerequisite that the distance from boundary. The line with the following higher accumulator value, which additionally satisfies the prerequisite that the separation from the past line is no less than 0.4 mm, is viewed as the media-adventitia limit. This separation quality was chosen in light of the clinical perception that the IMT is as a rule at any rate about 0.4mm in ordinary grown-ups. The IMT was computed as the separation between these two lines.The sensitivity (SE), specificity (SP) and accuracy (AC) were calculated as follows.

$$SE = TP\ D\ (TP + FN);$$
$$SP \quad TN\ D\ (TN + FP); \quad AC = (TP + TN)\ D\ N \qquad (7)$$

where the total number of pixels is N; TP is the number of true positive pixels, *i.e*., the pixels that automatic and manual segmentation matched as segmented; TN is the number of true negative pixels, *i.e*., the pixels that automatic and manual segmentation did not match as segmented; FP is the number of false-positive pixels, *i.e*., the pixels that automatic segmentation indicated as segmented, but manual segmentation did not; and FN is the number of false-negative pixels, *i.e*., the pixels that manual segmentation indicated as segmented, but automatic segmentation did not[11].

D. Normalization

Image normalization diminishes variability brought about by various gain settings, diverse operators, and distinctive hardware consequently permitting more reproducible gray scale estimations. Linear Histogram stretching was used for normalizing CCA ultrasound. For 8-bit images, the gray level estimation of blood was mapped to an estimation of 0, and the gray level of the center 2/fourth of the adventitia to an estimation of 190. Along these lines, ultrasound image power all through the image is rearranged by gray scale estimations of two reference locales (blood and adventitia). To keep up high reproducibility utilizing picture standardization, a delegate test of the adventitia is required. This is refined by imaging with the ultrasound beam propagating at right angles to the adventitia so it is noticeable contiguous the plaque.

4. FEATURE EXTRACTION AND OPTIMIZATION

Classification is more exact when the pattern is made simple through representation by essential features, feature extraction and determination assume a vital part in classifying frameworks, for example, neural systems. Distinctive feature extraction strategies were utilized to acquire feature vectors from ophthalmic and interior carotid artery ultrasound images. The issue of selecting significant features among the extracted features form the end goal of classification. Selection of features are based on one of these. (1) the perfect representation of a given class of signals, or (2) the perfect difference between classes[15]. Correlograms are histograms which measure not just insights about the components of the image, additionally consider the spatial distribution of these features. Two correlograms were actualized: 1) in view of the separation of the dispersion of the pixels gray level qualities from the focal point of the picture, and 2) in light of their angle of distribution. For every pixel the separation and angle from the image focus was ascertained and for all pixels with the same distance or angle their histograms were figured. Keeping in mind the end goal to make the examination between pictures of various sizes plausible, the separation correlograms were standardized into 32 conceivable separations from the middle by partitioning the computed separations with maximum_distance/32. The point of the correlogram was permitted to change among 32 conceivable qualities beginning from the left center of the picture and moving clockwise. The histogram and correlogram components were utilized for characterization with their original values while the other feature sets were normalized before use by subtracting their mean esteem and dividing with their standard deviation. The procedure for making Principal Component Analysis are to get the covariance matrix. Then get the Eigen Vectors and selecting top Eigen Values from Eigen Vectors[16].

V. CLASSIFICATION

The classification of ultrasound (US) pictures is especially troublesome, in light of the fact that US pictures have high speckle content, show non consistent intensities not withstanding for similar structures and normally have broken structural boundaries, separating US information from other imaging modalities utilized as a part of medical analysis. Literature reveals that neural systems can give more precise results concerning feature distinguishing. The diverse features that are obtained utilizing distinctive strategies are bolstered into the neural system framework and the outcomes so acquired are observed to be extremely reliable.

A. SOM & KNN Classifier

The neural self-organizing feature map (SOM) classifier can retrieve similar plaque images. It is an unsupervised learning algorithm where the input patterns are freely distributed over output matrix node. The density distribution of the input node must be protected and must be indicated in output node. So the weights are incorporated without supervision. Thus similar input nodes are mapped to output nodes which are nearby, indicates a discretization of the input, allowing a visualization of the distribution of input information. The output nodes are generally arranged in a two dimensional grid and toward the end of the training stage, the output nodes are marked with the class of most of the input patterns of the training set, allocated to every node. Using statistical k- nearest neighbor classifier (KNN), a new pattern can be classified, its k nearest neighbors are identified from the training set. Based on a similarity measure like Euclidean distance, the new pattern is classified to the most frequent class within its neighbors. Different k values and different feature sets can be used. Correlogram, Histogram and texture features gave best results for both the classifiers[17]. Morphological and shape feature set performed poor in both the types. Correlogram angle was the best feature set for this method with 74.3% exact retrievals followed by 74.1% for correlogram distance, 69.7% for histogram.

B. Multi-Layer Back Propagation Network system

Characteristics of network like number of hidden layers, processing elements in the individual layers, optimization technique and learning methods can be customized and accustomed to get good learning rate and least mean square error. Best results are obtained when the number of processing elements in the first hidden layer is three and nodes in second hidden layer is six[18]. Statistical features gave 95% results and wavelet features gave 97% correct results. Sensitivity and specificity were calculated using,

$$\text{Sensitivity} = \text{true positives}/(\text{true positives} + \text{false negative})$$
$$\text{Specificity} = \text{true negatives}/(\text{true negative} + \text{false positives}) \tag{8}$$

For MLBPN , the steps followed are as follows. 1. Data Scaling and Normalization. 2. Input data = original data/ normalization factor. Here, input data is the arterial thickness. 3. Original data = arterial thickness value. 4. Normalization factor = maximum value of the arterial thickness. Network Architecture Design and ANN learning algorithm are performed better with selected parameters and weights are determined. More inputs to train the algorithm, gives better output. Then optimum number of training iterations and hidden neurons are formulated by validation steps[19]. Training involves the following processes, 1.The data is preprocessed before the training process; 2.The weights are initialized; 3.For an input sample the outputs of both output and hidden layer is calculated; 4.Errors are calculated; 5.Weight values are adjusted according to error function. Training process depends on 3 learning coefficient (η), momentum (β), and mean square error (δmax)[20].

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6. CONCLUSION

Stroke is an important cause of death and leading reason for serious long term disabilities. It is caused by atherosclerosis, hardening of the artery walls and plaque formation. Ultrasound images of the carotid artery can be taken for analysis of Intima media thickness, lumen thickness and adventitia boundary. De-speckling is an important requirement in enhancement of ultrasonic images. The objective of this paper is to carry out a comparative evaluation of despeckling filters, segmentation techniques, optimal feature extraction and accurate classification of the ultrasound image as normal or abnormal. From literature, it is recognized that in future, more work is likely to be done to accomplish a fully automated system to identify plaque in ultrasound even in early stage of affect.

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