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An Effective Approach to Plaque Characterization in Ultrasound Images of Carotid Atherosclerosis

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Abstract

Stroke is one of the most important causes of death in the world and the leading cause of serious, long-term disability. There is an urgent need for better techniques to diagnose patients at risk of stroke. In order to increase the accuracy of the diagnosis, parameters aiming to identify vulnerable lesions have been studied using 2D B-mode ultrasound (US) imaging. This survey intends to summarize the techniques for improvement of Ultrasonographic image quality, extraction of good features and system for plaque classification from ultrasound images using image processing is described. The proposed system involves A Plaque Characterization method that use Wavelet Transform that favors extraction of important ultrasound structure which is associated with several risk factors for atherosclerosis and to develop a system for asymptomatic and symptomatic classification of the atherosclerotic carotid plaque in ultrasound images of the carotid artery.
Keywords- Atherosclerosis, Carotid Ultrasound, Classification, Discrete Wavelet Transform (DWT), Support Vector Machine (SVM)

I. INTRODUCTION

Atherosclerosis is accumulation of lipid, protein, and cholesterol esters, which significantly reduce blood flow.
Deposition of plaques results in thickening of arteries and leads to Atherosclerosis. Stroke increases with the severity of carotid stenosis, reduced after carotid endarterectomy. A stroke occurs usually when the blood supply to parts of the brain is suddenly interrupted or becomes blocked (Ischemic stroke). Ischemic strokes caused by artery stenosis, account for approximately 75% of all strokes. However, as a result of the above, a large number of patients are operated on unnecessarily.

Therefore, it is necessary to identify patients with a low risk who will be spared from an unnecessary, expensive and often dangerous operation. The primary aim of carotid image-processing is to provide human–independent aids for assessing the condition of the arteries and risk of stroke. In this Project, system for symptomatic vs. asymptomatic plaque classification from ultrasound images using image processing is described. This strategy may provide an important stage in the assessment of patients with asymptomatic carotid stenosis, making the clinical decision for surgical intervention easier. This reduces unnecessary anxiety in patients with asymptomatic plaques [7].

This paper provides an overview of plaque characterization techniques. The rest of this paper is organized as follows: Section 2 summarizes the general process flow, Section 3 provides the Survey on existing papers, Section 4 summarizes the proposed model and Section 5 shows results and Section 6 concludes the paper.

II. IMPLEMENTATION STAGES

The procedure of classification models is represented in below Figure 2.1

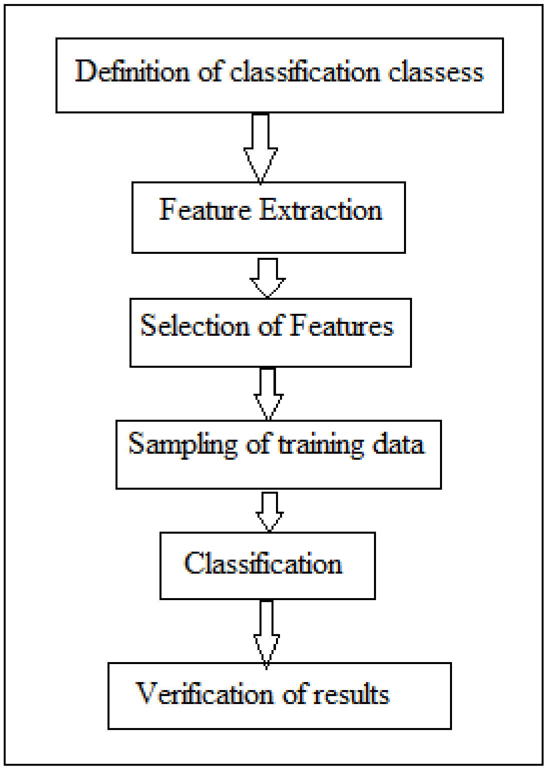


Fig. 2.1: Procedure of Classification Models

A. Methods

Typical symptomatic and asymptomatic carotid images are shown in Fig.2.2 (a) and (b).The plaques from patients having stroke, transient ischemic attack (TIA), and amaurosis fug ax (AF), were grouped as symptomatic plaques.

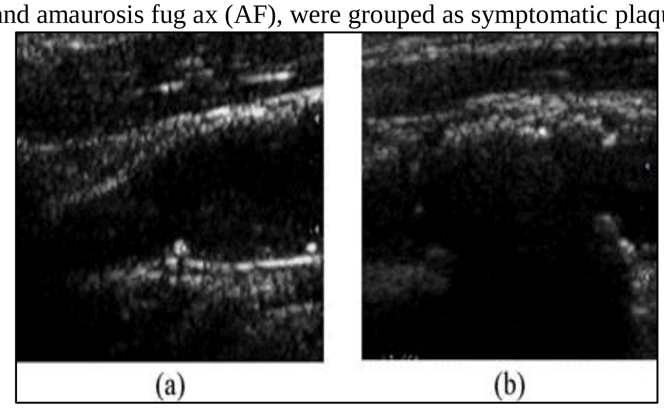


Fig. 2.2: Carotid images. (a) Symptomatic (AF). (b) Asymptomatic (AS)

Asymptomatic plaques were from patients who had no symptoms in the past. Feature Extraction is an area of image processing which involves using algorithms to detect and isolate various desired portions of a digitized image or video stream. When the input data to an algorithm is too large to be processed, then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called feature extraction. Some of the Feature Extraction techniques generally used are Principal component analysis, Multilinear subspace learning, Nonlinear dimensionality reduction, Isomap, Kernel PCA, Multilinear PCA, Latent semantic analysis, Partial least squares, Independent component analysis, Auto encoder, Thresholding, Hough transform Active contours (snakes), Edge detection. Feature selection is used to verify if the features are significant enough to be able to accurately discriminate the symptomatic and asymptomatic classes. Training data should be sampled in order to determine appropriate decision rules. Classification techniques such as supervised or unsupervised learning will then be selected on the basis of the training data sets. Image classification analyzes the numerical properties of various image features and organizes data into categories. Classification algorithms typically employ two phases of processing:

1) Training Phase

Characteristic properties of typical image features are isolated and, based on these, a unique description of each classification category is created.

2) Testing Phase

In the subsequent testing phase the feature-space partitions are used to classify image features.
Popular techniques are as follows.

1) Multi-level slice classifier
2) Minimum distance classifier
3) Maximum likelihood classifier
4) Other classifiers such as fuzzy set theory and expert systems.

The classified results should be checked and verified for their accuracy and reliability.

III. RELATED WORKS

This section provides a survey on the existing works.

N. Tsiaparas et al [1] proposed a model in which four different wavelet decomposition schemes; namely, the discrete wavelet transform, stationary wavelet transform, wavelet packets, and Gabor transform are used. The selected features were input into two classifiers using support vector machines (SVM) and probabilistic neural networks for the classification of morphological features of Carotid atherosclerotic plaque. Dominant texture features exhibited horizontal directionality, suggesting that texture analysis may be affected by biomechanical factors (plaque strains).Stationary wavelet transform is non-orthogonal and highly redundant, hence computationally expensive. Except WP, Other decomposition schemes constrained to low-frequency information which might not be adequate for classification.

J. Seabra, F. e Fernandes, and J. M. Sanches proposed a plaque classification framework for identifying symptomatic plaques [2]. The framework consists of image normalization, estimation of the envelope Radio-Frequency (eRF) image, de-speckling and speckle extraction

The purpose of this model is two-fold:

1) Build a plaque classification framework which uses a wide set of features, echo-morphology and texture parameters extracted after DE speckling algorithm.
2) Computed features in identifying symptoms in carotid plaques.

Speckle noise also limits the effective application of image processing and analysis algorithms (i.e., edge detection, segmentation). The authors proposed a system [3] which describes the clinical methods for visual classification, image segmentation, and denoizing. Several texture feature extraction and classification methods have been used. Image pre-processing includes image acquisition, normalization, DE speckling. The need for the accurate segmentation of the atherosclerotic carotid plague in ultrasound imaging in order to assess the degree of stenosis is, therefore, a very important task.

E. Kyriacou [4] proposed a model in which Normalized pattern spectra were computed for both a structural, multilevel binary morphological model, and a direct gray scale morphology model. This method follows image acquisition, normalization and segmentation of plaque images.

The derived pattern spectra were used as classification features with two different classifiers, PNN and SVM.

J. Stoitsis [6] proposed the system in which the combination of motion and texture features was shown to better characterize athermanous plaque. To reduce the dimensionality of the feature vector (99features), Analysis of Variance ANOVA was used. Fuzzy cmeans Classifier used to cluster motion and texture features.

Christodoulou [7] proposed a Multifeature Multiclassifier modular architecture model where Texture features and shape parameters were extracted from the segmented plaque images. Two different classifiers were used:

1) Neural network SOM
2) K-nearest neighbour (KNN)

IV. PROPOSED METHOD

The objective of the proposed work is to apply 2-D DWT (Discrete Wavelet Transform), to enhance the ultrasound image and aid in the identification, localization, and extraction, of this important ultrasound structure which is associated with several risk factors for atherosclerosis and to develop a system for asymptomatic and symptomatic classification of the atherosclerotic carotid plaque in 2D longitudinal ultrasound images of the carotid artery. Fig 4.1 shows the block diagram of the proposed system.

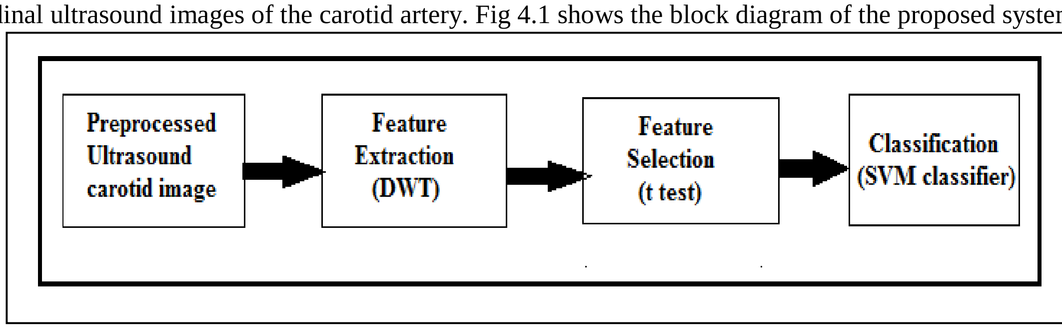


Fig. 4.1: Block Diagram of classification system

The proposed system uses DWT for feature extraction and can diagnose the two classes automatically with an accuracy, sensitivity, and specificity achieved that will be relatively higher than those recorded previous models in the literature. Feature extraction by 2-D DWT and averaging algorithms. The DWT transform of a signal x is determined by sending the signal through a sequence of down-sampling high- and low-pass filters.

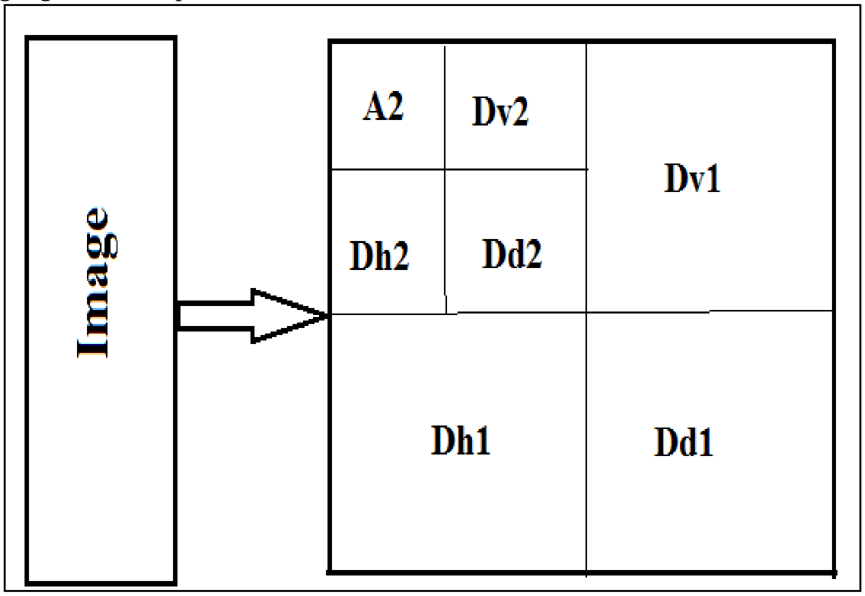


Fig. 4.2: Wavelet Based Image Decomposition

V. ALGORITHM FOR 2D-DISCRETE WAVELET TRANSFORM

Step 1: Define the low pass filter transfer function g[n] and high pass filter transfer function h[n].
Step 2: The signal 'x' is sent through a sequence of down sampling low-pass and high-pass filters. This result in the discrete wavelet transforms.
Step 3: For 2-D signals, this consists of DWT on rows of the image and a DWT on the columns of the resulting image.
Step 4: Details coefficients are defined as follows:

$$D[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k]$$

Step 5: Approximation coefficients are defined as follows:

$$A[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k]$$

Step 6: The decomposition of the image yields four sub images for every level. In every level time resolution is halved and frequency resolution in doubled.

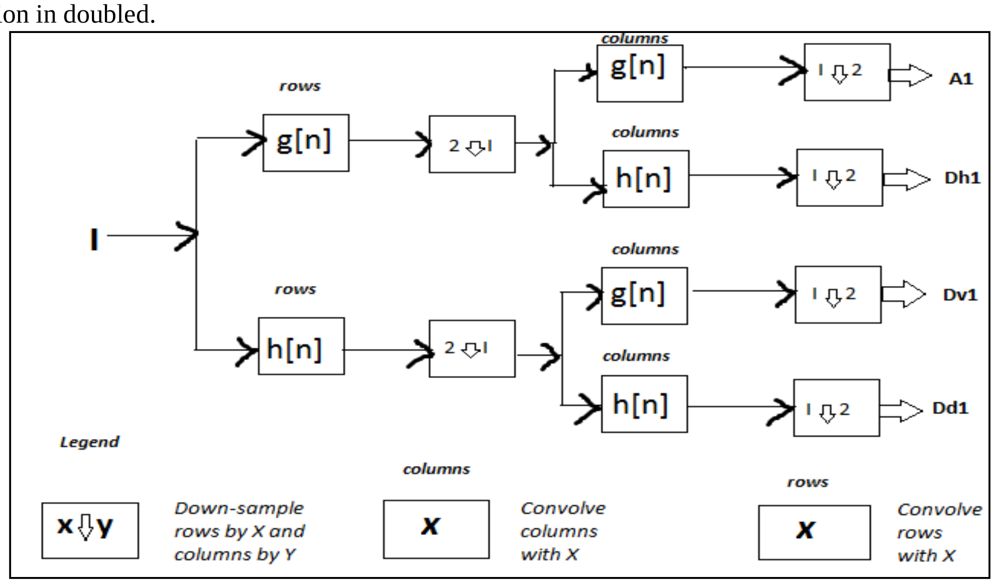


Fig. 4.3: Block diagram for implementation of Algorithm using DWT Decomposition

Each approximation subimage (Aj) is decomposed into four sub images [Aj+1, Dhj+1, Dvj+1, and Ddj+1], where 'j' represents the resolution levels as given in [1]. Each detail subimage is the result of a convolution with two half-band filters: a low-pass and a high-pass for Dhj , a high pass and a low-pass for Dvj , and two high-pass filters for Ddj. Bior3.1 performed better compared to the other wavelet functions.

The first-level 2-D DWT yields four result matrices, namely, Dh1, Dv1, Dd1, and A1, whose elements are intensity values. Unfortunately, these matrices cannot be used for classification directly because the number of elements is too high. Therefore two averaging methods which represent result matrices with just one number.

VI. AVERAGING ALGORITHMS

1) The first method is used to extract average measures from 2-D DWT result vectors.
2) The final averaging method uses averages not the intensity values as such but the energy of the intensity values.

The features selected were as follows: *energy* and *average horizontal* and *vertical* DWT coefficients. Average and Energy features are calculated using formulas

$$\text{Average Dh1(Ah)} = \frac{1}{N*M}\sum_{x=<N>}\sum_{y=<M>}|\text{Dh1}(x,y)| \qquad (4.1)$$

$$\text{Average Dv1(Av)} = \frac{1}{N*M}\sum_{x=<N>}\sum_{y=<M>}|\text{Dv1}(x,y)| \qquad (4.2)$$

$$\text{Energy(E)} = \frac{1}{N^2*M^2}\sum_{x=<N>}\sum_{y=<M>}\left(\text{Dv1}(x,y)\right)^2 \qquad (4.3)$$

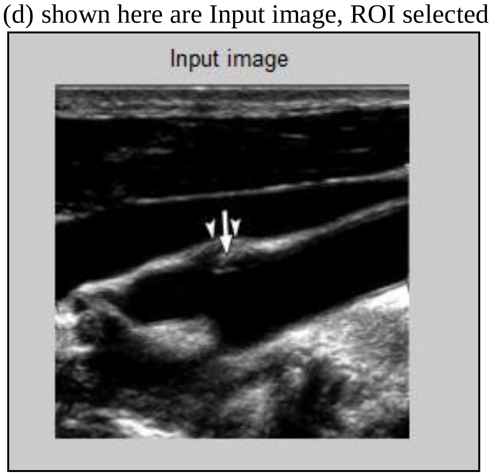
These three elements in equation (4.1), (4.2), (4.3) form the feature vector.
The statistical t-test technique used to select the suitable features for input to the classifiers.
In addition to performing linear classification, SVMs can efficiently perform non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

SVM is a hyper plane-based nonparametric classifier. During the testing of an unlabeled sample, the algorithm maps the sample into the same feature space and determines its class based on which side of the separating plane the sample is present. Thus, the main objective of SVM is to determine a separating hyper plane that maximizes In order to determine the margin, two parallel hyper planes are constructed, one on each side of the separating hyper plane, with the help of the training data. In order to determine the margin, two parallel hyper planes are constructed, one on each side of the separating hyper plane, with the help of the training data.The parameters calculated are:
TN- number of asymptomatic plaques identified as asymptomatic.
TP- number of symptomatic samples identified as symptomatic.
FN-number of symptomatic samples identified as asymptomatic.
FP-number of asymptomatic samples identified as symptomatic.

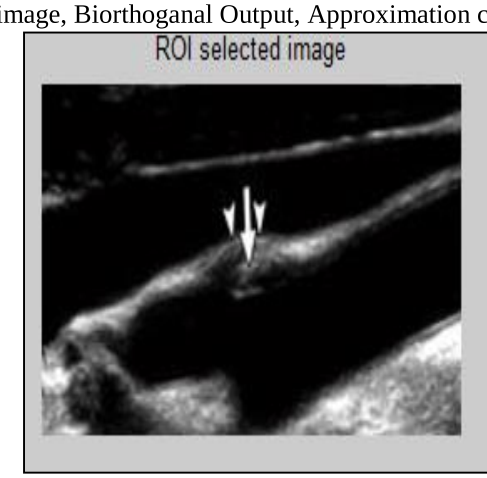
The performance measures for the classifier system are Sensitivity, Specificity, Accuracy and Positive Predictive value (PPV).Sensitivity, which is the probability that the technique will identify symptomatic cases, is calculated as TP/ (TP + FN).
Specificity, which is the probability that the technique will identify asymptomatic cases, is determined as TN/ (TN +FP).
PPV, which is the proportion of symptomatic subjects among those who were labeled symptomatic by the technique, is calculated as TP/(TP + FP).
Accuracy, which is the ratio of the number of correctly classified samples to the total number of samples, is calculated as (TP + FP)/(TP + FP + TN + FN).

VII. RESULTS

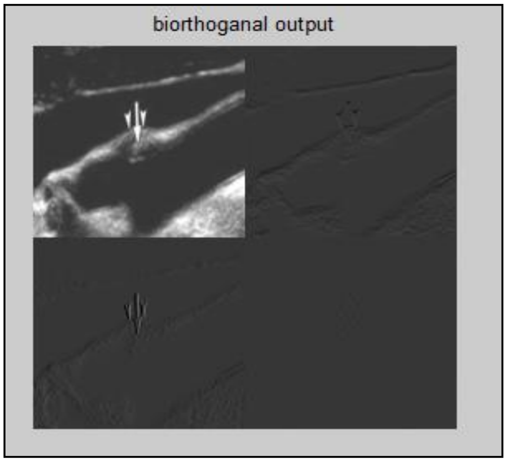
Fig (a), (b), (c) & (d) shown here are Input image, ROI selected image, Biorthoganal Output, Approximation component



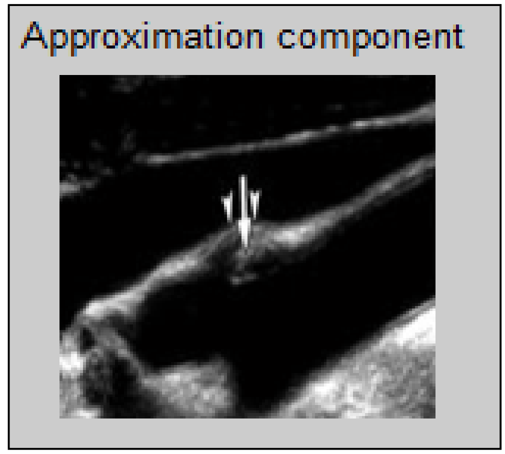
(a)



(b)



(c)



(d)

Features are then extracted from the approximation image and classification done.

VIII. CONCLUSION

The classification of carotid plaque is a difficult and multifaceted problem. The present proposed system overcomes some of these problems. The system uses two Dimensional Discrete Wavelet transform for feature extraction and can diagnose the two classes automatically, hence serve as an efficient adjunct tool for the vascular surgeons in selecting patients for risky stenosis treatments. These extracted features can then be fed to a simple support vector machine classifier and Plaque characterization can be obtained.

The feature set is small only three features yet is powerful enough for classification. Not only reduces the cost associated with procedures like CAS and CEA but also reduces the unnecessary anxiety in patients with asymptomatic plaques. SVM classifier with the polynomial kernel of order 2 would achieve an average improved accuracy. The technique is low cost as it is based on only features extracted from the ultrasound image and there is absolutely no cost needed for deployment in the doctor's office. Moreover, the technique does not use radiation unlike computed tomography and is much economic unlike magnetic resonance imaging.

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