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Automatic Segmentation of Carotid Intima-Media Thickness using SRAD Filter and Analysis of Significant Features

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ABSTRACT

Intima–Media Thickness (IMT) of Common Carotid Artery (CCA) is widely accepted and validated marker of progression of disease called atherosclerosis. Ultrasound imaging is commonly used non-invasive tool used to detect border and measurement of IMT for the assessment of cardiovascular diseases. In this work, an attempt has been made to improve the visual perception for automated analysis by comparing Gaussian, Speckle Reduction Anisotropic Diffusion (SRAD), Wavelet filters in terms of quantitative metrics. A completely automated Otsu's thresholding based algorithm is applied for segmentation of Intima–Media Layer and texture features are extracted for analysis. Results show that filter performs better in smoothing uniform regions and preserving edges and features. The proposed segmentation technique showed automatic measurements of thickness of near wall with mean and standard deviation of 0.501±0.072mm obtained with manual values 0.515±0.087mm and for far wall 0.484±0.079 with manual values 0.458±0.074mm for normal CCA. For abnormal CCA the proposed technique for near wall showed mean and standard deviation values of 0.899±0.197mm and manual 0.854±0.140mm, and for far wall 1.548±1.478mm and manual values of 1.706±1.66mm. The correlation coefficient between manual and automatic showed 0.97 for near wall and 0.98 for far wall in normal arteries, 0.94 for near wall and 0.91 for far wall in abnormal arteries. Texture features such as grey scale median, cluster prominence and cluster shade showed most significant($p<0.0001$) to differentiate normal from atherosclerosis subjects. Hence this method could help the physician in assessment of stroke risk in carotid ultrasound images.

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INTRODUCTION

Cardiovascular diseases like coronary artery disease, peripheral artery disease and cerebral vascular diseases are ranked by World Health Organisation as the third leading cause of death and adult disability in the industrial world (American Heart Association, 2015). The incidence of cardiovascular disease is increasing over the age of 65. It is estimated that there will be 23 million deaths due to atherosclerosis that will be associated with coronary heart disease and stroke by 2030. Atherosclerosis is a systemic disease with the progressive development of Intima-Media Thickness (IMT) in Common Carotid Artery (CCA). IMT is the distance between the lumen-intima and media-adventia interface along the walls of the carotid arteries. IMT is considered as the valid marker of progression of the disease and commonly used measure in clinical practice. Ultrasound (US) has long been recognized as a powerful tool for use in the diagnosis and evaluation of many clinical entities. Ultrasound imaging has become one of the most utilized modalities in characterization of carotid plaques and assessment of carotid artery disease. Carotid IMT has been shown to correlate with severity of the atherosclerosis and predict cardiovascular events independent of traditional risk factors (Lorenz, M.W., 2007; Ishizu, T., 2002) and can be evaluated quantitatively, noninvasively and with low cost, using high resolution B-mode ultrasound.

Speckle is a form of multiplicative and correlated noise in medical ultrasound imaging application. This noise is more difficult to remove than additive noise, because the intensity of the noise varies with the image intensity. In automatic segmentation, maintaining the sharpness of the boundaries between different image regions is significant while removing the speckle. Speckle noise has a significant impact on the correctness of boundary detection. The edges of the adventia are

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also affected by this noise. Thus, it is essential to develop despeckle filters which can preserve the features that are of interest (Jappreet Kaur, *et al*., 2011). It is used as the pre-processing step to reduce noise effect in the artery lumen.

Accurate measurements of the IMT and the plaque in the carotid arteries are therefore important for the estimation and management of the risk of stroke. Trained operators are required to perform manual measurements. The intima-media borders are usually traced manually by experts but it is time consuming, and results show poor reproducibility. A review of the recent methods for US processing and segmentation exploiting chan-vese model was proposed by E.Angelini *et al*. (2005) and G. Slabaugh *et al*. (2009). The development and testing of new methods for computing the IMT will greatly help experts in the estimation of the carotid artery disease.

There are a number of automated and semi automatic segmentation techniques for Intima-Media Complex (IMC) which have been proposed. Segmentation using gradient, edge-based techniques, dynamic programming techniques, Snake based technique extraction of texture and other image features have been proposed (Christos, P., 2009; Loizou, C.P., 2007). Segmentation of CCA using Hough transform is proposed in (Golemati, S., 2007). Recently integrated method using edge detection and curve fitting to estimate the adventia boundary and dynamic programming with intensity thresholding have been used to estimate the lumen boundary (Loizou, C.P., 2011). An automatic segmentation algorithm using active contour with edges (Kass, M., 1988) and active contours without edges (Chan and L. Vese, 2001) was developed. Nasrui *et al*. (Nasrul Humaimi Mahmood and Eko Supriyanto, 2011) presented an automatic detection using thresholding method which showed 90% accuracy. The different age groups of patients have different deep locations of carotid artery, hence automatic detection becomes difficult. Otsu's thresholding method is used for segmentation detects edges in carotid arteries without blurring the image which is very important especially in medical image. In threshold based method there is no need for common point to set the software to automatically detect the arteries.

C.P.Loizou *et al*. (2011) investigated the progression of texture characteristics through the use of multi scale AM(Amplitude Modulation)-FM(Frequency Modulation) methods.GSM feature is related to historical feature of the plaque such as elastin and calcium content of the plaque. The GSM is the strong predictor of future events of stroke. The grey scale median of the ultrasound plaque image was used for characterisation of plaques as echolucent (GSM≤32) and echogenic (GSM>32). Based on this texture features the atherosclerosis subjects can be classified as stable and unstable plaques.

In this work, an attempt has been made to evaluate the performance of Gaussian, Speckle Reducing Anisotropic Diffusion (SRAD), Wavelet-denoising filters for the US image of the carotid artery. Filter suitable for removing speckle and preserving the useful information like edges is selected based on performance metrics (Jessika Andersson, 2009). From the filtered image IMT is measured automatically using Otsu's segmentation technique. The initialization procedure is completely eliminated. The result of fully automated segmentation is valid against expert clinicians with manual intima-media layer segmentation and IMT measures. The proposed technique highly correlates with the manual values and also reduces the computational time. The texture features are extracted from the segmented image and these features are used to differentiate normal and atherosclerosis subjects. Also based on the texture features the plaque is characterized into stable and unstable plaques. Significant features are selected using principle component analysis.

II. Methodology:

2.1. Acquisition of Ultrasound Images and manual measurements:

The database consisting of 40 B-mode longitudinal ultrasound images of CCA is used for the evaluation of IMT. The carotid ultrasound examination was performed using a Philips IU22 ultrasound system equipped with linear array transducers of L9-3MHz. The images are captured at optimal distance with centre frequency of 6MHz.Twenty normal subjects and twenty patients suffering from atherosclerosis were considered for the study. The subject's age ranged from 35 to 77 years (average: 52.3 years, standard deviation: 5.4years). The images were recorded from Global Hospitals and Health city, Chennai. A neurovascular expert delineated manually the IMT using the mouse. The IMT was measured by selecting the consecutive points. The measured points and delineations were saved for comparison with the proposed method.

2.2 Speckle Removal:

Speckle is a form of multiplicative noise caused when the surface image appears rough to the scale of the wavelength used. It limits the performance of automated computer analysis algorithms. An attempt has been made to evaluate the performance of the despeckle filters on ultrasound carotid images

2.2.1. Gaussian filter:

Gaussian smoothing is very effective for the removal of Gaussian noise. Filtering is done with 3x3 masks. The weights are computed according to a Gaussian function

$$G(x,y)=\frac{1}{2\pi\sigma^2}\exp(-(x^2+y^2))/2\sigma^2 \qquad (1)$$

The weights give higher significance to pixels near the edges. It has computationally efficient and rotationally symmetric properties. The degree of smoothing is controlled by σ, the standard deviation.

2.2.2. Speckle Reduction Anisotropic Diffusion Filter:

Anisotropic diffusion creates scale space ,where more and more blurred images is generated successively based on diffusion process The resulting image is the combination of the original image and a filter that depends on the local content of original image. SRAD is a partial differential equation approach that generates an image scale space, a set of filtered images that vary from fine to course.

$$\partial I(x,y;t)/\partial t = div[p(q)\Delta I(x,y;t)] \tag{2}$$

$$I(x,y;0) = I_0(x,y), (\partial I(x,y;t)/\partial \underset{n}{\rightarrow})\big|\partial\Omega = 0 \tag{3}$$

$\partial\Omega$ is the border of Ω and $p(q)$ is shown in equation (4)

$$p(q) = \frac{1}{1+\left[q^2(x,y;t)-q_0^2(t)\right]/\left[q_0^2(t)(1+q_0^2(t))\right]} \tag{4}$$

$$p(q) = \exp\left\{-\left[q^2(x,y;t)-q_0^2(t)\right]/q_0^2(t)(1+q_0^2(t))\right\} \tag{5}$$

$q(x,y;t)$ is the instantaneous coefficient of variation given as in equation (6) The speckle scale function $q_0(t)$ is given in equation (7). The instantaneous coefficient of variation $q(x,y;t)$ serves as the edge detector. The speckle scale function $q_0(t)$ controls the amount of smoothing applied to the image.

$$q(x,y;t) = \sqrt{\frac{(\frac{1}{2})(\frac{|\Delta I|^2}{I}) - (\frac{1}{4^2})(\frac{|\Delta^2 I|}{I})^2}{\left[1+(\frac{1}{4})(\frac{|\Delta^2 I|}{I})^2\right]}} \tag{6}$$

$$q_0(t) = \frac{\sqrt{\mathrm{var}[z(t)]}}{\overline{z(t)}} \tag{7}$$

where var $z(t)$ and $\overline{z(t)}$ are the intensity variance and mean over a homogenous area at t, respectively.

2.2.3. Wavelet de-noising filter:

Discrete Wavelet Transform (DWT) is performed for noisy images and wavelet coefficients are obtained. Noise variance is estimated for noisy images. High-frequency component of the image is the speckle noise that appears in wavelet coefficients and wavelet thresholding is calculated. Wavelet thresholding is one among the technique for speckle reduction. The noisy image is decomposed into wavelet basis and to despeckle the image the wavelet coefficients are zeroed out. Here a soft-thresholding function is used in which values slightly below the threshold are not set to zero but merely attenuated. Soft-thresholding is chosen because in frayed edges are avoided leading to more visually pleasant images. Inverse DWT is performed to reconstruct denoised image.

2.2.4. Performance evaluation of despeckle filters:

Despeckle filters is used to preserve the useful information like edges and point features and can be evaluated using parameters such as Peak-Signal-to-Noise Ratio (PSNR), Mean-Squared-Error (MSE), Normalized Cross Correlation (NCC) and Normalized Absolute Error (NAE) (Nasrul Humaimi Mahmood and Eko Supriyanto, 2011). The mean square error measures the quality change between the original and the processed image in MXN window. The PSNR is higher for a better-transformed image and lower for a poorly transformed image. It measures the image fidelity very well.

Filters like Gaussian, wavelet-denoising and Speckle Reducing Anisotropic Diffusion filter are applied on ultrasound carotid artery image. The performances metrics are calculated for the filters and compared as shown in the Table I. The filters have been tested upon 40 ultrasound images of the carotid artery.

2.2.4. Segmentation of the IMT by Otsu method:

A completely automatic threshold based segmentation technique is attempted in this work. This has been done for 40 ultrasound images of the carotid artery collected from patients of different age groups normal (N=20) and abnormal (N=20).

The algorithm for the proposed Otsu segmentation method is as follows:

Based on threshold the pixels are separated into two clusters.

The mean of each cluster is calculated.

The differences between the means are squared. The number of pixels in one cluster times is multiplied by the number in the other. The histogram and probabilities is computed for each intensity level. Within-class variance and class mean values are determined initially. Stepping through all possible thresholds of maximum intensity the within-class variance and the class means are updated. The between-class variances are calculated. Desired threshold is corresponding to the maximum value.

The estimation of class probabilities are as

$$q_1(t) = \sum_{i=1}^{t} P(i) \tag{8}$$

$$q_2(t) = \sum_{i=t+1}^{I} P(i) \tag{9}$$

And the class means are given by,

$$\mu_1(t) = \sum_{i=1}^{t} \frac{iP(i)}{q_1(t)} \tag{10}$$

$$\mu_2(t) = \sum_{i=t+1}^{I} \frac{iP(i)}{q_2(t)} \tag{11}$$

The weighted within class variance is,

$$\sigma_w^2(t) = q_1(t)\sigma_1^2(t) + q_2(t)\sigma_2^2(t) \tag{12}$$

The weighted between class variance is

$$\sigma_b{}^2(t) = q_1(t)[1-q_1(t)][\mu_1(t)-\mu_2(t)]^2 \tag{13}$$

Finally, the individual class variances are given by

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$$\sigma_1^2(t) = \sum_{i=1}^{t} [i - \mu_1(t)]^2 \frac{P(i)}{q_1(t)} \quad (14)$$

$$\sigma_2^2(t) = \sum_{i=t+1}^{I} [i - \mu_2(t)]^2 \frac{P(i)}{q_2(t)} \quad (15)$$

Total variance is the sum of the within-class variance and the between class variance

$$\sigma^2 = \underbrace{\sigma_w^2(t)}_{\text{Within class variance}} + \underbrace{q_1(t)[1-q_1(t)][\mu_1(t)-\mu_2(t)]^2}_{\text{Between class variance}} \quad (16)$$

Minimizing the within class variance is the same as maximizing the between class variance Otsu's method assigns pixels to foreground or background based on gray scale intensity. A thresholding algorithm based on Otsu's thresholding method is developed that computes the threshold value automatically.

The manual and automatic methods were compared the inter method error were calculated according to the formula s=Standard Deviation (SD)√2 and $\bar{x}$ is the mean value of IMT .The coefficient of variation (CV) describes the percentage difference between two methods according to the formula CV=(s/$\bar{x}$)*100%.

2.2.5. Texture analysis of the carotid plaque:

First order statistics is used to analyze plaque deposited in the carotid artery. The parameters are derived directly from the gray level histogram. The mean, GSM, Energy values were shown in Table III. The measurement of GSM has become a reproducible measurement of overall plaque echo density.

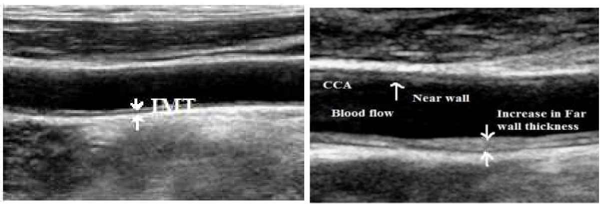
Neighbourhood Gray Tone Difference Matrices (NGTDM) that corresponds to visual properties of the textures such as coarseness, contrast, complexity, busyness and strength are extracted.

The spatial relationship of pixels in the image is considered for extracting Gray Level Co-Occurrence Matrices (GLCM). The texture measures computed in this category are: correlation, contrast, energy and homogeneity. Spatial Gray Level Dependence Matrices (SGLDM) is based on joint conditional probability density functions. Autocorrelation, contrast, correlation, cluster prominence, cluster shade, dissimilarity, energy, maximum probability, sum of square variance, sum average, sum entropy, difference variance, sum variance, sum average, difference variance, sum variance, difference entropy and information measure of correlation.

The above mentioned 30 texture features for normal and abnormal images are extracted. The most significant features are shown in the Table I. Based on the features extracted the classification of stable and unstable plaques could be made. Unstable plaques are symptomatic and heterogeneous. They are darker, higher contrast, rougher, less periodical echolucent, less coarse. Stable plaques are asymptomatic, bright, less contrast, more smooth, more periodical, echogenic and more coarse.

RESULTS AND DISCUSSIONS

Fig.1 shows the typical normal and abnormal B-mode longitudinal ultrasound images of carotid artery .In longitudinal view the length and thickness of the intima media layer is seen. In the middle the channel is appreciated as dark area where the blood flows called lumen. The figure also shows the far wall with increased thickness.



(a) (b)

Fig. 1: shows the anatomical structure of (a)Normal (b)Abnormal Common carotid artery.

Despeckle filters like Gaussian, SRAD and Wavelet are applied for ultrasound images as shown in figure 2(a-h) respectively. Fig.2 a& b are original image and (c-h) are filtered images. It is observed that the Gaussian filtered images Fig.2c & d and wavelet de-noised images shown in Fig.2g & h do not enhance edges; they only restrain smoothing near the edges. When any portion of the filter window contains an edge, the coefficient of variation is high and smoothing is subdued in that portion. Therefore speckle in the neighbourhood of an edge remains even after filtering. SRAD filter shown in Fig.2e&f preserves edges and also enhances by inhibiting diffusion across edges and allowing diffusion on either side of the edge.

The performance metrics were evaluated for despeckle filters and measured quantitatively using Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Normalized Cross Correlation (NCC) and Normalized Absolute Error (NAE) shown in Table I. It is observed from the results that the average value for Gaussian and SRAD filters exhibits better performance in terms of the performance metrics than wavelet denoising filter. The SRAD filter shows better performance and clear edges of the intima- media layer. Anisotropic diffusion seems to be an efficient, nonlinear technique for simultaneously performing contrast enhancement and noise reduction.

It retains image edges and smoothes homogeneous image regions. Expert assessed best visual results were obtained by the SRAD filter. Fig.3 presents the automatic segmentation of the IMT using Otsu's method. The thickness is evaluated for the near and far wall layers of the arteries. Average and standard deviation values are shown in Table II for near and far wall. The difference between manual and the proposed method is calculated.

The results show higher correlation between the manual and proposed method. The coefficient of variation is calculated. Fig.3 (a-j) shows the segmentation of near wall and far wall of CCA. The abnormal images show clear edges with increase in thickness of intima-media layer. The proposed automatic segmentation method show good correlation with the manual method. The coefficient of variation showed less than 5.6% in normal and less than 4% for atherosclerosis subjects.

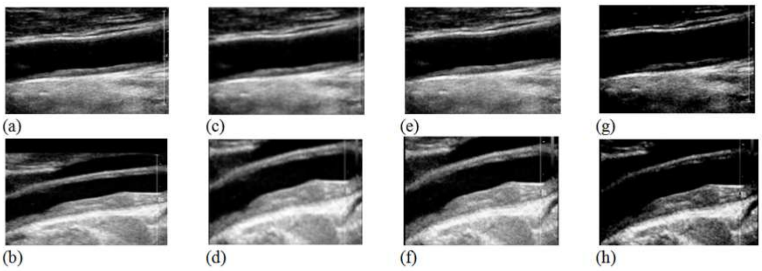


Fig. 2: (a-b) Original abnormal images (c-d) Gaussian filtered image (e-f) SRAD filtered image (g-h)Wavelet denoised image.

Table I: Performance Metrics With Average And Standard Deviation For Speckle Filters.

Performance Metrics	Gaussian	SRAD	Wavelet
PSNR	27.46	47.48	10.86
MSE	21.73	0.0011	5.74
NCC	0.95	0.214	0.0016
NAE	0.115	0.81	0.988

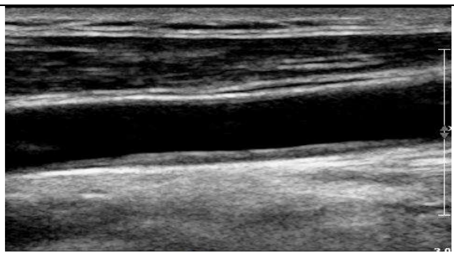
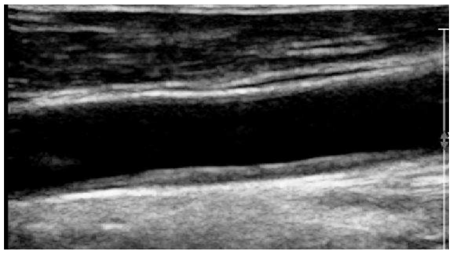
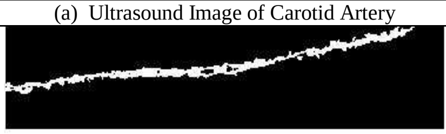
	
(a) Ultrasound Image of Carotid Artery	(b) Carotid artery image using SRAD filter
	
(c)Segmented near wall Intima-Media Layer	(d)Segmented far wall Intima-Media Layer

Fig. 3: Automatic segmentation of carotid artery (a) Ultrasound Image of Carotid Artery (b) Carotid artery image using SRAD filter (c) Segmented near wall Intima-Media Layer (d) Segmented far wall Intima-Media Layer.

Table III shows the most significant features extracted from the normal and abnormal images using First order Statistics, SGLDM, NGDTM, and GLCM. The features GSM, coarseness, contrast, cluster prominence, cluster shade, energy and maximum probability are found to be significant in differentiating the normal and atherosclerosis subjects. The Gray Scale Median (GSM) is found to be most significant feature in first order statistics.

The GSM value is used to characterize plaque into stable and unstable in atherosclerosis subjects. GSM values which the potential biomarker is associated with increased risk of stroke.The decrease in GSM values may be attributed to the accumulation of calcium (ecogenic) that occurs in the process of atherosclerosis at its early stages. Fig. 4 shows mean values of GSM for 20 abnormal subjects of far wall. From the results the mean values of GSM <32(N=3) shows the higher risk of stenosis causing transient ischemic attack or stroke. The GSM values >32(N=5) and GSM >70(N=12) may be attributed to lower risk with ecolucent plaques also the values was found to decrease with increase in patients age.

The Fig 5 shows the comparison of differentiation in normalized values of significant features like cluster prominence, cluster shade, energy and maximum probability of far wall. The results show that normalized average value of cluster prominence, energy and maximum probability significant features is higher in abnormal images due to pathological conditions and cluster shade show higher in normal.

Table II: Comparison Between Manual And Automated System.

	Manual system(mm)	Automated System(mm)	Difference(mm)	CV (%)	Correlation (r)
	Mean±SD	Mean±SD	Mean±SD		
	Common carotid artery Normal subjects (N=20)				
IMT mean(near wall)	0.515±0.087	0.501±0.072	0.014±0.015	5.09	0.97
IMT mean(far wall)	0.458±0.074	0.484±0.079	0.026±0.005	5.58	0.98
	Common carotid artery Abnormal subjects (N=20)				
IMT mean(near wall)	0.85±0.14	0.899±0.1965	0.045±0.0565	3.9	0.94
IMT mean(far wall)	1.706±1.66	1.548±1.478	0.158±0.182	1.2	0.91

SD-standard deviation, CV-Coefficient of variation

The most significant features are also analyzed using Principal Component Analysis (PCA). The magnitude of most significant features in first two principal components is shown in fig 6a & b. Cluster prominence and cluster shade showed higher differentiation between normal and atherosclerosis subjects. It is observed that angle between energy and maximum probability is less and angle between cluster shade and other three parameters are high. This shows independent nature of the cluster shade feature with respect to other features. The feature cluster shade could be used as significant feature for classification of mass data base images.

Hence the proposed automatic segmentation reproduced IMT measurements by the radiology expert and reduced considerable time compared to manual measurements.

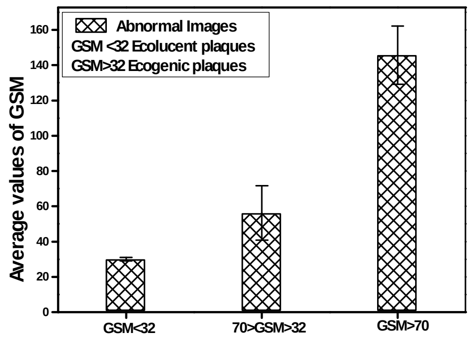


Fig. 4: Mean values of GSM for abnormal images of far wall.

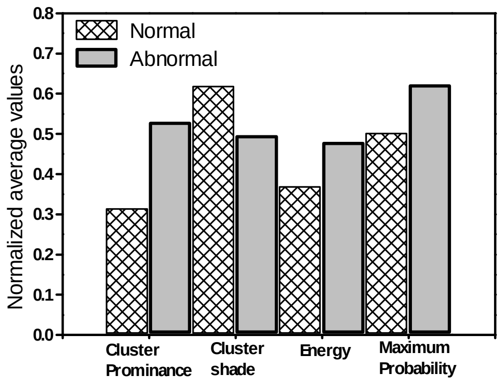
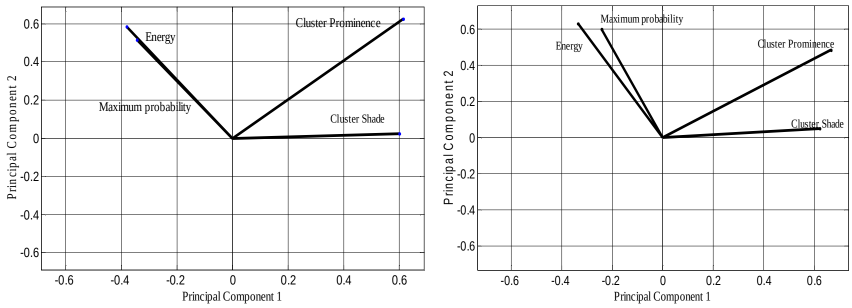


Fig. 5: Comparison of variation in the normalized values of significant features of far wall.

Table III: Texture Features For Normal And Atherosclerosis Subjects.

Texture features	Normal (N=20)		Abnormal(N=20)	
	Near wall	Far wall	Near wall	Far wall
First order statistics				
GSM*	0.383±0.265	0.4130±0.244	0.639±0.455	0.561±0.4536
Neighbourhood Gray Tone Difference Matrix (NGTDM)				
Coarseness*	0.6198±0.182	0.580±0.256	0.775±0.253	0.709±0.205
Contrast*	0.416±0.271	0.446±0.215	0.678±0.221	0.727±0.232
Gray Level Co-occurrence Matrix(GLCM)				
Contrast*	0.157±0.081	0.180±0.072	0.180±0.114	0.281±0.166
Spatial Gray Level Dependence Matrices(SGLDM)				
Cluster Prominence*	0.438±0.309	0.315±0.317	0.48±0.306	0.53±0.33
Cluster Shade*	0.154±0.537	0.620±0.350	0.301±0.370	0.497±0.347
Energy*	0.614±0.194	0.370±0.288	0.580±0.251	0.480±0.250
Maximum probability*	0.636±0.183	0.503±0.265	0.501±0.236	0.623±0.190
*Most significant features(p<0.0001)				



(a) (b)

Fig. 6: Variation in component magnitudes of selected GLCM features with the first four principal components for (a) normal and (b) abnormal images.

V. Conclusion:

Ultrasound imaging is the most frequently performed method for the diagnosis of cardiovascular diseases. The clinical diagnosis depends upon the accuracy, performance of the measured and predicted values. In this study an attempt has been made to estimate the quantitative ability of speckle filters in despeckling the ultrasound B –mode images. This improves the image quality and visual interpretation as well as automated performance of the algorithm. Speckle reducing anisotropic diffusion filter is used as the pre-processing step which showed better performance evaluation by preserving the edges. The automatic segmentation using Otsu’s method can be used successfully in measurement of IMT complementing the manual measurements without initializing procedure. The results show that proposed method highly correlates with manual and also reduces overall analysis time. The IMT values show the level of deposition of plaque. Thus it appears that based on significant features extracted GSM, cluster prominence and cluster shade group of patients at risk of stroke could be classified and medicated.

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