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Segmentation of the Ultrasound Carotid Intima-Media layer and Analysis of the Carotid Plaque Texture Features

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***Abstract*:** The intima–media thickness (IMT) of the carotid artery (CA) and the size and consistency of the plaque deposited in the carotid artery are widely accepted and validated markers of progression of Atherosclerosis and of onset of cardiovascular disorders. IMT is usually measured by using ultrasound imaging. Several algorithms have been proposed for the segmentation of ultrasound carotid artery intima-media, but almost all require a certain degree of user interaction. Also speckle, a form of multiplicative, locally correlated noise, corrupts medical ultrasound imaging applications. The objective of this paper is to (i) identify an efficient and optimum despeckle filter in terms of quantitative metrics to be applied to ultrasound carotid artery making it more suitable for further processing (ii) describe a completely automated threshold based technique for carotid intima–media layer segmentation and (iii) analyze the ultrasonic carotid plaque texture features to characterize the different types of plaque. In this paper, Lee, Kuan, Wavelet de-noising and Speckle reducing Anisotropic Diffusion (SRAD) filters have been tested in detail on ultrasound carotid artery images. To assess the performance of filters, quantitative metrics such as Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Normalised Cross Correlation (NCC) and Normalized Absolute Error (NAE) have been calculated. The results of applying the speckle reducing anisotropic diffusion (SRAD) despeckle filter followed by Otsu's thresholding based segmentation algorithm showed promising results to be used for IMT measurements. The accuracy of the proposed technique is verified by comparing the IMT measurements obtained from the proposed technique with the manual IMT values. Also texture analysis of the plaque that gets deposited in the carotid artery due to Atherosclerosis is performed. Based on the texture features the plaque could be characterized into stable and unstable plaques. The plaque characterization is to be done as future work. This will help avoid unnecessary and dangerous surgical interventions and facilitate in giving more precise treatment to the patients leading to their safety.

Index Terms: *Anisotropic Diffusion, Atherosclerosis, Carotid Artery, Carotid Plaque, Otsu's thresholding, Intima-media thickness, Texture analysis*

I. Introduction

Measurements of the intima-media thickness (IMT) of the carotid artery (CA) by ultrasound have been used in several clinical trials to validate atherosclerosis disease, where measurements from 0.4mm to 0.7mm are considered to be normal and values greater than 0.7mm indicate atherosclerosis development [1] and future cardiovascular events. Also differences in the structure and composition of atherosclerotic plaques i.e. plaque morphology, is directly associated with future health problems of patients [1]. It is necessary to identify which plaques can be referred to as safe and which has the potential to rupture and threaten the patient's life. 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. Segmentation of the carotid artery is an important operation before further analysis such as IMT measurement can take place as it will simplify the analysis. The intima-media borders are usually traced manually by experts but it is time consuming, and results show poor reproducibility. The development and testing of new methods for computing the IMT will greatly help experts in the estimation of the carotid artery disease. In the segmentation of an ultrasound image of the carotid artery, concern lies in identifying and measuring the IMT based on which the presence or absence of plaque is determined. In this paper a completely automatic threshold based segmentation of the carotid artery is proposed. To determine the thresholding level, Otsu's thresholding method [2] is used. Also despeckle filtering [3]-[6] is implemented to reduce the speckle noise [3]. Intima-media thickness (IMT) measurement is made by measuring the thickness of the wall of the segmented artery.

II. DESPECKLE FILTERING

Speckle noise, is a major performance-restraining factor in ultrasound imaging as it limits the effective application of automated computer analysis algorithms. Speckle 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. Thus, it is essential to develop despeckle filters which can preserve the features that are of interest. Here an attempt is made in evaluating the performance of four despeckle filters on ultrasound carotid artery images; Lee [3], Kuan [3], Wavelet-denoising [3][4] and Speckle Reducing Anisotropic Diffusion (SRAD) [3][5] filters in terms of performance metrics [6]; Peak-Signal-to-Noise ratio (PSNR), Mean-Squared-Error (MSE), Normalized Cross Correlation (NCC) and Normalized Absolute Error (NAE) and also based on their edge preserving property.

A. Lee Filter

The output of the Lee filter is a linear combination of the center pixel intensity in the filter window and the average intensity of the window as in (1). The filter achieves a balance between simple averaging (in homogeneous regions) and the identity filter (where edges and point features exist). This balance depends on the coefficient of variation inside the moving window.

$$I_0(i, j) = I_m + W \times \left(C_p - I_m\right) \qquad (1)$$

where, I_0 is the pixel value at indices i, j after filtering, I_m is mean intensity of the filter window, C_p is the center pixel and W is a filter window given by (2).

$$W = \frac{\sigma^2}{\sigma^2 + \rho^2} \qquad (2)$$

σ^2 is the variance of the pixel values within the filter window and is calculated as in (3) where, N is the size of the filter window, X_j is the pixel value within the filter window at indices j. The parameter ρ is the additive noise variance of the image given in (4) where, M is the size of the image, Yj is the value of each pixel in the image.

$$\sigma^2 = \left[\frac{1}{N}\sum_{j=0}^{N-1}\left(X_j\right)^2\right] \qquad (3)$$

$$\rho^2 = \left[\frac{1}{M}\sum_{i=0}^{M-1}\left(Y_i\right)^2\right] \qquad (4)$$

B. Kuan Filter

Kuan filter is a local linear minimum square error filter based on multiplicative order that models the speckle noise into an additive linear form. The weighting function W is computed as in (5).

$$W = \frac{\left(1 - \frac{C_u}{C_i}\right)}{(1 + c_u)} \qquad (5)$$

The weighting function is computed from the estimated noise variation coefficient of the image C_u given in (6).

$$C_u = \sqrt{\frac{1}{ENL}} \qquad (6)$$

ENL is the effective number of looks that specifies the degree of averaging of the filter. C_i is the variation coefficient of the image computed as in (7)

$$C_i = \frac{S}{I_m} \qquad (7)$$

where, S is the standard deviation of the filter window, Im is mean intensity value within the window.

C. Wavelet de-noising Filter

Speckle noise is a high-frequency component of the image and appears in wavelet coefficients. So a method for speckle reduction is wavelet thresholding procedure. The image is decomposed into wavelet basis and the wavelet coefficients are zeroed out to despeckle the image. The basic procedure as in for all thresholding methods is, 1. Calculate DWT of the image 2.Threshold the wavelet components 3. Compute IDWT to obtain denoised estimate. 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 soft thresholding frayed edges are avoided leading to more visually pleasant images.

D. Speckle Reducing Anisotropic Diffusion (SRAD) Filter

Anisotropic diffusion [5] creates a scale space, where a family of successively more and more blurred images is generated based on a diffusion process. Each resulting image in this set is a combination of the original image and a filter that depends on the local content of the original image. SRAD [5] is an anisotropic diffusion method for removing speckle in images. SRAD is a Partial Differential Equation (PDE) approach that generates an image scale space; a set of filtered images that vary from fine to course. For an intensity image $I_0(x, y)$ having finite power and no zero values over the image support Ω, the output image I(x, y; t) is evolved according to the PDE in (8).

$$\partial I(x,y;t)/\partial t = div[c(q)\Delta I(x,y;t)] \qquad (8)$$

$$I(x,y;0) = I_0(x,y), (\partial I(x,y;t)/\partial \vec{n})|\partial\Omega = 0 \qquad (9)$$

$\partial\Omega$ is the border of Ω, $\vec{n}$ is the outer normal to the $\partial\Omega$ and c(q) is given as in (10) or in (11).

$$c(q) = \frac{1}{1+\left[q^2(x,y;t)-q_0^2(t)\right]/\left[q_0^2(t)(1+q_0^2(t))\right]} \qquad (10)$$

$$c(q) = \exp\left\{-\left[q^2(x,y;t)-q_0^2(t)\right]/q_0^2(t)(1+q_0^2(t))\right\} \qquad (11)$$

q(x, y; t) is the instantaneous coefficient of variation given as in (12). $q_0(t)$ is the speckle scale function as given in (13). 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.

$$q(x,y;t) = \sqrt{\frac{(\frac{1}{2})(\frac{|\Delta I|^2}{I}) - (\frac{1}{4^2})(\frac{|\Delta^2 I|}{I})^2}{\left[1+(\frac{1}{4})(\frac{|\Delta^2 I|}{I})^2\right]}} \qquad (12)$$

$$q_0(t) = \frac{\sqrt{\mathrm{var}[z(t)]}}{\overline{z(t)}} \qquad (13)$$

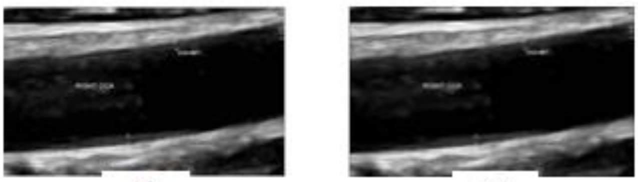
var $z(t)$ and $\overline{z(t)}$ are the intensity variance and mean over a homogenous area at t, respectively.

III. PERFORMANCE EVALUATION OF DESPECKLE FILTERS

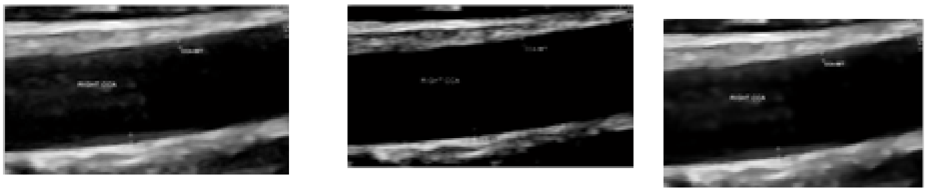
The quality of the despeckle filters in terms of their efficiency in removing speckle and preserving the useful information like edges and point features can be objectively measured in terms of parameters such as PSNR, MSE, NCC and NAE performance metrics [6]. Their mathematical expressions are presented in Table 1.

TABLE I PERFORMANCE METRICS

Performance Metrics	Formula
\Mean-Squared Error	$MSE = \frac{1}{N\times M}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}[X(i,j)-Y(i,j)]^2$
Peak-Signal-to-Noise Ratio	$PSNR = 10\log_{10}\frac{L^2}{MSE}$
Normalized Cross Correlation	$NCC = \frac{\sum_{x,y} X(x,y).Y(x,y)}{\sum_{x,y} Y^2(x,y)}$
Normalized Absolute Error	$NAE = \frac{\sum_{x,y} X(x,y)-Y(x,y)}{\sum_{x,y} Y^2(x,y)}$



(a) (b)



(c) (d) (e)

Figure 1 Original and despeckled images of carotid artery (a) Original image (b) Lee Filter with 3x3 window (c) Kuan Filter with 3x3 window (d) Wavelet de-noising Filter (e) SRAD Filter

The results after implementing the despeckle filters on an ultrasound carotid artery image is shown in Figure 1. The performance metrics calculated for the four filters applied to the carotid image in Figure 1 is listed out in Table 2. The filters have been tested upon 14 ultrasound images of the carotid artery. The efficiency of the despeckle filters in terms of their edge preserving characteristic is analyzed.

The Lee and Kuan filters are sensitive to the size of the filter window. A large filter window size over-smoothes and the edges get blurred. A small window decreases the smoothing capability of the filter and leaves some speckle. Here a window size of 3X3 has been found appropriate and used for both the Lee and Kuan. The Lee, Kuan and Wavelet de-noising filters 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 neighborhood of an edge remains even after filtering.

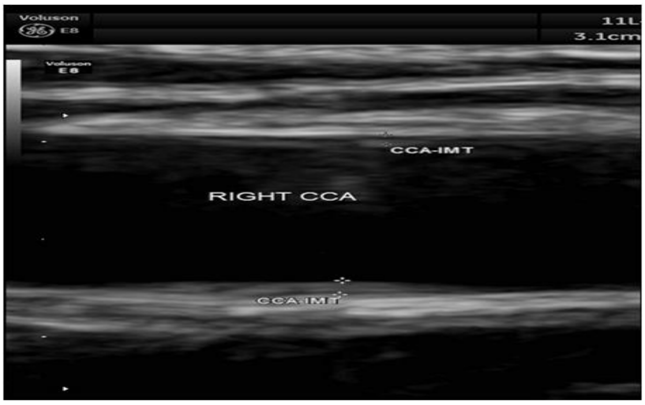
The speckle reducing anisotropic diffusion (SRAD) filter shows no bias to filter window size. SRAD not only preserves edges but also enhances edges by inhibiting diffusion across edges and allowing diffusion on either side of the edge. Also the SRAD filter exhibits better performance in terms of the performance metrics as shown in Table 2 and also proved the same for all the 14 ultrasound carotid images. The PSNR values are clearly higher for the SRAD filter compared to the others. In this sense, we extend the application of SRAD filter to be used as the despeckle filter to remove the speckle noise present in ultrasound images of the carotid artery that is to be used for further steps of segmentation and texture analysis.

TABLE 2 PERFORMANCE METRICS OF THE IMPLEMENTED DESPECKLE FILTERS CORRESPONDING TO IMAGES SHOWN IN FIGURE 1

DESPECKLE FILTER	PERFORMANCE METRICS			
	MSE	PSNR	NCC	NAE
LEE (3X3)	6.5536	39.9660	0.9945	0.0265
KUAN(3X3)	15.6754	36.1786	0.9870	0.0513
WAVELET	5.3775	10.8250	0.0017	0.9987
SRAD	1.1658	47.4645	0.2132	0.8253

IV. SEGMENTATION OF THE IN TIME-MEDIA

A completely automatic threshold based segmentation technique is attempted in this paper. This has been done for 14 ultrasound images of the carotid artery collected for patients of different age groups of which 9 are normal carotid images and 5 are plaque deposited carotid images. The segmentation method used here is Otsu's thresholding method [2]. The ultrasound image is first converted to grayscale image. Otsu's method assigns pixels to foreground or background based on grayscale intensity. The key step in the thresholding process is the choice of the threshold value. A thresholding algorithm based on Otsu's thresholding method is developed that computes the threshold value automatically. It iterates through all the possible threshold values and calculates a measure of spread for the pixel levels at each side of the threshold, i.e. the pixels that either falls in foreground or background. The aim is to find the threshold value where the sum of foreground and background spreads is at its minimum i.e to find the threshold that minimizes the weighted within-class variance [2]. This is the same as maximizing the between-class variance [2]. It operates directly on the gray level histogram of the image. The pixels are separated into two clusters according to the threshold. The mean of each cluster is found and the square of the difference between the means is calculated. It is multiplied by the number of pixels in one cluster times the number in the other. The histogram and probabilities of each intensity level is computed. An initial value for the class probability and the class mean $q_i(0)$ and $\mu_i(0)$ is set up. All the possible threshold values with maximum intensity are examined and then q_i and μ_i are updated. Finally the between-class variance $\sigma_b^2(t)$ is computed and the desired threshold corresponds to the maximum value. In the thresholding process, individual pixels in the image are marked as object pixels (i.e. pixels in the intima–media layer of the carotid artery), if their value is greater than the threshold value assuming an object to be brighter than the background and as background pixels otherwise. The object pixel is given a value of 1 while a background pixel is given a value of 0 thus forming a binary image. After the thresholding process, in the binary image obtained all the pixels smaller than the value 800 are removed by using morphological operations. In the morphologically processed image, the holes that occur in the desired portion are filled. After all these steps, the intima-media layer of the carotid artery is successfully segmented out. The results of segmentation are shown in Figure 2. The thickness of the segmented intima-media layer is measured in mm. The measured IMT values are compared with the manual IMT values. The comparison results are shown in Table 3. Though there are slight differences in the values the results are quite promising and there is no overlap between the normal and the plaque IMT values.



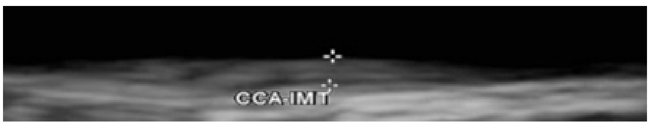
(a)

(b)

(c)

(d)

(e)



(f)

(g)

(h)

(i)

Figure 2 Carotid Intima-Media layer Segmentation (a) Despeckled Carotid Artery Image using SRAD Filter (b) Cropped upper portion of carotid artery (c) Binarized image of Upper Intima-Media layer (d) Smaller pixels removed Image (e) Segmented Upper Intima-Media layer (f) Cropped lower portion of carotid artery (g) Binarized image of Lower Intima-Media layer (h) Smaller pixels removed Image (i) Segmented Lower Intima-Media layer

TABLE 3 COMPARISON OF THE MANUAL AND PROPOSED TECHNIQUE IMT VALUES

	Manual IMT (mm)		Proposed IMT (mm)	
	Upper wall	Lower wall	Upper wall	Lower wall
1	0.51	0.45	0.5027	0.4762
2	0.55	0.50	0.5556	0.5027
3	0.38	0.42	0.3704	0.4233
4	0.52	0.55	0.4700	0.5500
5	0.41	0.43	0.4724	0.5820
6	0.44	0.34	0.5290	0.3175
7	0.66	0.58	0.6085	0.5291
8	0.57	0.40	0.5027	0.4497
9	0.61	0.46	0.5820	0.5291
10	0.50	0.72	0.4175	0.7143
11	1.05	2.98	1.1641	2.6193
12	0.92	4.68	1.0054	4.0745
13	0.86	0.98	0.9089	0.9524
14	0.71	0.66	0.7143	0.4600

V. TEXTURE ANALYSIS OF THE CAROTID PLAQUE

The texture of the plaque deposited in the carotid artery is analyzed based on the first and second order statistics. First order statistics depend only on individual pixel values and not on interaction of neighboring pixel values. Second-order statistics are calculated from the probability of observing a pair of pixel values in the image. Here an attempt is made to extract at least 30 texture features based on the following algorithm methods,

1. First Order Statistics (FOS)
2. Spatial Gray Level Dependence Matrices (SGLDM)
3. Neighborhood Gray Tone Matrices (NGDTM)
4. Fractal Dimensional Texture Analysis (FDTA)
5. Gray Level Co-occurrence Matrices (GLCM)

In First order statistics [7] the parameters are derived directly from the gray level histogram. These describe the gray level distribution without considering spatial independence and as a result describe echogenicity of texture and the overall variation characteristics within the region of interest (ROI). The texture measures computed are: Mean, standard deviation, gray scale median (GSM) and Energy.

The SGLDM [8] algorithm is based on the theory that texture properties of an image are contained in the overall or average spatial relationship between the gray levels in the image. SGLDM is based on the estimation of the second order conditional probability density f(i,j;d,q). Each value f(i,j;d,q) represents the probability that two different resolution cells which are in the direction specified by an angle q and have distance d, will have gray level values i and j respectively. The texture measures from this category are: Contrast, Correlation, Shadow, Dissimilarity, Energy, Sum of Squares, Homogeneity, Sum Average, Sum Variance, Sum Entropy, Entropy, Difference Variance, and Difference Entropy.

The NGDTM [8] algorithm is used to extract texture features that correspond to the visual properties of texture. The texture measures computed in this category are Coarseness, Contrast, Complexity, Busyness and Strength. FDTA [9] is an approach that correlates between texture coarseness and fractal dimension.

The texture measures computed in this category are: Information Measure of Correlation-1 (InM1) and Information Measure of Correlation-2 (InM2), Inverse Difference Moment (IDM) Correlation and Inverse Difference Normalized Correlation. GLCM [10] method considers the spatial relationship of pixels in the image. The GLCM methods characterize the texture of an image by calculating how often pairs of pixel with specific values and a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. The texture measures computed in this category are: Correlation, Contrast, Energy and Homogeneity.

The above mentioned algorithms have been used to extract the ultrasonic plaque texture features of 5 plaque images. These are listed in Table 4. As future work, the most suitable features to characterize the plaque are to be found and based on these features, the different types of plaque is yet to be characterized.

VI. CONCLUSION

The results show that the carotid artery has been segmented out efficiently after the application of the SRAD despeckle filter. Also the plaque texture features are extracted. As future work the plaque is to be characterized based on these texture features and based on the results proper treatment could be suggested for patients leading to increased patient safety.

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TABLE 4 TEXTURE FEATURES OF CAROTID PLAQUE.

TEXTURE FEATURE (mm)	PLAQUE 1	PLAQUE 2	PLAQUE 3	PLAQUE 4	PLAQUE 5
FIRST ORDER STATISTICS					
Mean	49,464	95409	20671	16089	18196
Gray Scale Median (GSM)	100	62.75	127	87	49
Energy	11037696	501859	98990	82932	23561
SPATIAL GRAY LEVEL DEPENDENCE					
Correlation	9.5403	5.6596	6.3537	9.8612	7.2172
Contrast	0.3562	0.7657	0.4628	0.5367	0.2479
Shadow	10.4814	11.4820	9.8579	5.8345	9.4926
Dissimilarity	0.2813	0.3206	0.2736	0.3069	0.1794
Energy	0.1659	0.2092	0.1924	0.1499	0.1949
Entropy	2.2883	2.1009	2.1164	2.3048	2.0211
Homogeneity	0.8683	0.8781	0.8804	0.8686	0.9183
Maximum Probability	0.3264	0.3227	0.3012	0.2884	0.3324
Sum of Squares	9.5650	5.9640	6.5722	10.2742	7.1435
Sum Average	5.4191	4.2851	4.5213	5.6992	4.7439
Sum Variance	20.4757	11.1274	12.3982	20.8375	14.2880
Sum Entropy	2.0539	1.8182	1.8824	2.0472	1.8774
Difference Variance	0.3562	0.7657	0.4628	0.5367	0.2479
Difference Entropy	0.6436	0.6834	0.6281	0.6784	0.4960
NEIGHBORHOOD GRAY TONE					
Coarseness	9.1252	26.5558	17.2618	31.1628	18.1245
Contrast	1.0200	0.5678	0.4760	0.4089	0.8219
Complexity	132684	137213	169643	80922	165500
Strength	677210	597105	643072	903848	425516
Busyness	0.000009	0.000002	0.000006	0.000003	0.000004
GRAY LEVEL CO-OCCURRENCE					
Contrast	0.1657	0.5717	0.2403	0.3043	0.1935
Correlation	0.9738	0.8492	0.9356	0.9401	0.9601
Energy	0.1942	0.2290	0.2227	0.1789	0.2002
Homogeneity	0.9626	0.9497	0.9603	0.9477	0.9666
FRACTAL DIMENSIONAL TEXTURE					
Information Measure of Correlation-1 (InM1)	-0.5875	-0.5234	-0.5529	-0.5634	-0.6686
Information Measure of Correlation-2 (InM2)	0.9233	0.8806	0.8955	0.9143	0.9331
Inverse Difference Normalized Correlation	0.9695	0.9682	0.9713	0.9680	0.9807
Inverse Difference Moment (IDM) Correlation	0.9948	0.9906	0.9938	0.9926	0.9964