Despeckle filtering in ultrasound imaging of the carotid artery

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Despeckle Filtering in Ultrasound Imaging of the Carotid Artery

2.1 INTRODUCTION

The use of ultrasound in the diagnosis and assessment of arterial disease is well established because of its non-invasive nature, its low cost, and the continuing improvements in image quality [1]. Speckle, a form of locally correlated multiplicative noise corrupts medical ultrasound imaging making visual observation difficult [2], [3]. The presence of speckle noise in ultrasound images has been documented since the early 1970’s where researchers such as Burckhardt [2], Wagner [3], and Goodman [4], described the fundamentals and the statistical properties of the speckle noise. Speckle is not truly a noise in the typical engineering sense, since its texture often carries useful information about the image being viewed. It is the primary factor, which limits the contrast resolution in diagnostic ultrasound imaging, thereby limiting the detectability of small, low contrast lesions and making the ultrasound images generally difficult for the non-specialist to interpret [2], [3], [5], [6]. Due to the speckle presence, ultrasound experts with sufficient experience may not often draw useful conclusions from the images [6]. Speckle noise also limits the effective application of image processing and analysis algorithms (i.e. edge detection, segmentation) and display in 2D and volume rendering in 3D. Therefore, speckle is most often considered a dominant source of noise in ultrasound imaging and should be filtered out [2], [5], [6] without affecting important features of the image. The objective of this work was to carry out a comparative evaluation of despeckle filtering techniques based on texture analysis, image quality evaluation metrics as well as visual assessment by experts on 440 ultrasound images of the carotid artery bifurcation. Results of this study were also published in [7], [8] and [9]. This chapter was also published in a longer paper in [9].
The wide spread of mobile and portable telemedicine ultrasound scanning instruments also necessitates the need for better image processing techniques, in order to offer a clearer image to the medical practitioner. This makes the use of efficient despeckle filtering a very important task. Early attempts to suppress speckle noise were implemented by averaging of uncorrelated images of the same tissue recorded under different spatial positions [5], [10], [11]. While these methods are effective for speckle reduction, they require multiple images of the same object to be obtained [12]. Speckle reducing filters originated from the synthetic aperture radar (SAR) community [10]. These filters have then later been applied to ultrasound imaging since the early 1980’s [13]. Filters that are used widely in both SAR and ultrasound imaging include the Frost [14], Lee [10], [15], [16], and Kuan [12], [17].

Table 2-1 summarizes the despeckle filtering techniques that are investigated in this study, grouped under the following categories: local statistics, median filtering, homogeneity, geometric, homomorphic, anisotropic diffusion and wavelet filtering. Furthermore, in Table 2-1 the main investigators, the methodology used and the corresponding filter names are given. These filters are briefly introduced in this Section, and presented in greater detail in Section II.

Some of the local statistic filters are the Lee [10], [15], [16], the Frost [14], and the Kuan [12], [17]. The Lee and Kuan filters have the same structure, whereas the Kuan is a generalization of the Lee filter. Both filters form the output image by computing the central pixel intensity inside a filter-moving window, which is calculated from the average intensity values of the pixels and a coefficient of variation inside the moving window. Kuan considered a multiplicative speckle model and designed a linear filter, based on the minimum-mean-square error (MMSE) criterion that has optimal performance when the histogram of the image intensity is Gaussian distributed. The Lee [10] filter is a particular case of the Kuan filter based on a linear approximation made for the multiplicative noise model. The Frost [14]
Despeckle filtering in ultrasound imaging of the carotid artery makes a balance between the averaging and the all-pass filters. It was designed as an adaptive Wiener filter that assumed an autoregressive exponential model for the image.

TABLE 2-1 [here]
In the homogeneity group the filtering is based on the most homogeneous neighbourhood around each image pixel [8], [9]. Geometric filters [11] are based on non-linear iterative algorithms, which increment or decrement the pixel values in a neighbourhood based upon their relative values. The method of homomorphic filtering [18], [19] is similar to the logarithmic point operations used in histogram improvement, where dominant bright pixels are de-emphasised. In the homomorphic filtering, the FFT of the image is calculated, then denoised, and then the inverse FFT is calculated.

Some other despeckle filtering methods, such as anisotropic diffusion [2], [20], [21]-[24] speckle reducing anisotropic diffusion [5] and coherence anisotropic diffusion [25] presented in the literature, are non-linear filtering techniques for simultaneously performing contrast enhancement and noise reduction by utilising the coefficient of variation [5]. Furthermore, in the wavelet category, filters for suppressing the speckle noise were documented. These filters are making use of a realistic distribution of the wavelet coefficients [2], [16], [26]-[31] where only the useful wavelet coefficients are utilised. Different wavelet shrinkage approaches were investigated, usually based on Donoho’s work [30].

The majority of speckle reduction techniques have certain limitations that can be briefly summarised as follows:

1. They are sensitive to the size and shape of the window. The use of different window sizes greatly affects the quality of the processed images. If the window is too large over smoothing will occur, subtle details of the image will be lost in the filtering process and edges will be blurred. On the other hand, a small window will decrease
the smoothing capability of the filter and will not reduce speckle noise thus making the filter not effective.

2. Some of the despeckle methods based on window approaches require thresholds to be used in the filtering process, which have to be estimated empirically. The inappropriate choice of a threshold may lead to average filtering and noisy boundaries thus leaving the sharp features unfiltered [7], [11], [15].

3. Most of the existing despeckle filters do not enhance the edges but they only inhibit smoothing near the edges. When an edge is contained in the filtering window, the coefficient of variation will be high and smoothing will be inhibited. Therefore, speckle in the neighbourhood of an edge will remain after filtering. They are not directional in the sense that in the presence of an edge, all smoothing is precluded. Instead of inhibiting smoothing in directions perpendicular to the edge, smoothing in directions parallel to the edge is allowed.

4. Different evaluation criteria for evaluating the performance of despeckle filtering are used by different studies. Although most of the studies use quantitative criteria like the mean-square error (MSE) and speckle index (C), there are additional quantitative criteria, like texture analysis and classification, image quality evaluation metrics and visual assessment by experts that could be investigated.

To the best of our knowledge there are only two studies that investigated despeckle filtering on ultrasound images of the carotid artery. In [5], speckle reducing anisotropic diffusion as the most appropriate method was proposed. This technique was compared with the Frost [14], Lee [15], and the homomorphic filtering [19] and documented that anisotropic diffusion performed better. In [32] a pre-processing procedure was first applied to the ultrasound carotid artery image, which modified the image so that the noise becomes very close to white Gaussian. Then filtering methods based on additive model may be applied. Three different
filters namely the wavelet, the total variation filter, and anisotropic diffusion were applied before and after the image modification, and showed that the quality of the image was improved when these are applied after the noise was modified to Gaussian.

In this study, we compare the performance of 10 despeckle filters on 440 ultrasound images of the carotid artery bifurcation. The performance of these filters was evaluated using, texture analysis, the kNN classifier, image quality evaluation metrics, and visual evaluation by two experts. The results of our study, show that despeckle filtering improves the class separation between asymptomatic and symptomatic ultrasound images of the carotid artery.

In the following Section, a brief overview of despeckle filtering techniques is presented, whereas in Section III the methodology is presented, covering the material, recording of ultrasound images, texture and statistical analysis, the kNN classifier, image quality evaluation metrics and the experiment carried out for visual evaluation are described. Sections IV and V present the results, and discussion respectively.

2.2 DESPECKLE FILTERING

In order to be able to derive an efficient despeckle filter, a speckle noise model is needed. The speckle noise model may be approximated as multiplicative, if the envelope signal which is received at the output of the beam former of the ultrasound imaging system, is captured before logarithmic compression and may be defined as:

\[ y_{i,j} = x_{i,j}n_{i,j} + a_{i,j} \] (2.1)

where \( y_{i,j} \) represents the noisy pixel in the middle of the moving window, \( x_{i,j} \) represents the noise-free pixel, \( n_{i,j} \) and \( a_{i,j} \) represent the multiplicative and additive noise, respectively, and \( i, j \) are the indices of the spatial locations that belong in the 2D space of real numbers, \( i, j \in \mathbb{R}^2 \). Logarithmic compression is applied to the envelope detected echo signal in order to fit it in the display range [25], [33]. It has been shown, that the logarithmic compression,
affects the speckle noise statistics in such a way that the local mean becomes proportional to the local variance rather than the standard deviation [25], [27], [29], [33] (see also (8)). More specifically, logarithmic compression affects the high intensity tail of the Rayleigh and Rician probability density function (PDF) more than the low intensity part. As a result the speckle noise becomes very close to white Gaussian noise corresponding to the uncompressed Rayleigh signal [33]. Since the effect of additive noise is considerably smaller compared with that of multiplicative noise, equation (1) may be written as:

\[ y_{i,j} \approx x_{i,j} n_{i,j}. \]  

Thus the logarithmic compression transforms the model in (2) into the classical signal in additive noise form as:

\[ \log(y_{i,j}) = \log(x_{i,j}) + \log(n_{i,j}), \]  

\[ g_{i,j} = f_{i,j} + nl_{i,j}. \]  

For the rest of the work the term \( \log(y_{i,j}) \), which is the observed pixel on the ultrasound image display after logarithmic compression, is denoted as \( g_{i,j} \), and the terms \( \log(x_{i,j}) \), \( \log(n_{i,j}) \) which are the noise free pixel and noise component after logarithmic compression, as \( f_{i,j} \) and \( nl_{i,j} \) respectively (see Eq. 3b).

2.4.10 Local statistics filtering

Most of the techniques for speckle reduction filtering in the literature use local statistics. Their working principle may be described by a weighted average calculation using sub region statistics to estimate statistical measures over different pixel windows varying from 3x3 up to 15x15. All these techniques assume that the speckle noise model has a multiplicative form as given in (2) [7]-[17], [25], [27].
2.4.10.1 First Order Statistics Filtering (lsmv, wiener)

The filters utilizing the first order statistics such as the variance and the mean of the
neighbourhood may be described with the model as in (3). Hence the algorithms in this class
may be traced back to the following equation [5], [7]-[18]:

\[ f_{i,j} = \bar{g} + k_{i,j}(g_{i,j} - \bar{g}) \] (2.4)

where \( f_{i,j} \) is the estimated noise-free pixel value, \( g_{i,j} \) is the noisy pixel value in the moving
window, \( \bar{g} \) is the local mean value of an \( N_1 \times N_2 \), region surrounding and including pixel
\( g_{i,j} \), \( k_{i,j} \) is a weighting factor, with \( k \in [0..1] \), and \( i, j \) are the pixel coordinates. The factor
\( k_{i,j} \), is a function of the local statistics in a moving window. It can be found in the literature
[9], [10], [12], [15] and may be derived in different forms that:

\[ k_{i,j} = (1 - \bar{g}^2 \sigma^2) / (\sigma^2 (1 + \sigma^2_n)) \] (2.5)

\[ k_{i,j} = \sigma^2 / (\bar{g}^2 \sigma^2_n + \sigma^2) \] (2.6)

\[ k_{i,j} = (\sigma^2 - \sigma^2_n) / \sigma^2 \] (2.7)

The values \( \sigma^2 \), and \( \sigma^2_n \), represent the variance in the moving window and the variance of
noise in the whole image respectively. The noise variance may be calculated for the
logarithmically compressed image, by computing the average noise variance over a number of
windows with dimensions considerable larger than the filtering window. In each window the
noise variance is computed as:

\[ \sigma^2_n = \sum_{i=1}^{p} \sigma^2_p / \bar{g}_p \] (2.8)

where \( \sigma^2_p \), and \( \bar{g}_p \), are the variance and mean of the noise in the selected windows
respectively and \( p \), is the index covering all windows in the whole image [9], [25], [26], [33].

If the value of \( k_{i,j} \), is 1 (in edge areas) this will result to an unchanged pixel, whereas a value
of 0 (in uniform areas) replaces the actual pixel by the local average, $\overline{g}$, over a small region of interest (see (4)). In this study the filter $lsmv$ uses equation (5). The filter $wiener$ uses a pixel-wise adaptive Wiener method [2]-[6], [14] implemented as given in (4), with the weighting factor $k_{i,j}$, as given in (7). For both despeckle filters $lsmv$ and $wiener$ the moving window size was 5x5.

2.4.10.2 Homogeneous Mask Area Filtering ($lsminsc$)

The $lsminsc$ is a 2D filter operating in a 5x5 pixel neighbourhood by searching for the most homogenous neighbourhood area around each pixel, using a 3x3 subset window [9], [34]. The middle pixel of the 5x5 neighbourhood is substituted with the average gray level of the 3x3 mask with the smallest speckle index, $C$, where $C$ for log-compressed images is given by:

$$C = \frac{\sigma^2}{\overline{g}}$$

where $\sigma^2$, and $\overline{g}$, represents the variance and mean of the 3x3 window. The window with the smallest $C$ is the most homogenous semi-window, which presumably, does not contain any edge. The filter is applied iteratively until the gray levels of almost all pixels in the image do not change.

2.4.11 Median Filtering ($median$)

The filter $median$ [35] is a simple nonlinear operator that replaces the middle pixel in the window with the median-value of its neighbours. The moving window for the $median$ filter was 7x7.

2.4.12 Maximum Homogeneity Over a Pixel Neighbourhood Filtering ($homog$)

The $homog$ filter is based on an estimation of the most homogeneous neighbourhood around each image pixel [9], [36]. The filter takes into consideration only pixels that belong in the
processed neighbourhood (7x7 pixels) using (10), under the assumption that the observed area is homogeneous. The output image is then given by:

$$f_{i,j} = \left( c_{i,j} g_{i,j} \right) / \sum_{i,j} c_{i,j} , \quad \text{with} \quad c_{i,j} = 1 \text{ if } (1 - 2\sigma_g) \bar{g} \leq g_{i,j} \leq (1 + 2\sigma_g) \bar{g}$$

$$c_{i,j} = 0 \quad \text{otherwise} .$$

The *homog* filter does not require any parameters or thresholds to be tuned, thus making the filter suitable for automatic interpretation.

### 2.4.13 Geometric Filtering (gf4d)

The concept of the geometric filtering is that speckle appears in the image as narrow walls and valleys. The geometric filter, through iterative repetition, gradually tears down the narrow walls (bright edges) and fills up the narrow valleys (dark edges), thus smearing the weak edges that need to be preserved.

The *gf4d* filter [11] investigated in this study, uses a non-linear noise reduction technique. It compares the intensity of the central pixel in a 3x3 neighbourhood with those of its 8 neighbours and, based upon the neighbourhood pixel intensities it increments or decrements the intensity of the central pixel such that it becomes more representative of its surroundings.

The operation of the geometric filter *gf4d* may be described with Fig. 2-1 and has the following form:

1. Select direction and assign pixel values
   Select the direction be NS and the corresponding three consecutive pixels be $a$, $b$, $c$ (see Fig. 2-1a and 2-1b respectively).

2. Carry out central pixel adjustments
   Do the following intensity adjustments (see Fig. 2-1b)

   \[
   \text{if } a \geq b + 2 \text{ then } b = b + 1 ,
   \]
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if \(a > b\) and \(b \leq c\) then \(b = b + 1\),
if \(c > b\) and \(b \leq a\) then \(b = b + 1\),
if \(c \geq b + 2\) then \(b = b + 1\),
if \(a \leq b - 2\) then \(b = b - 1\),
if \(a < b\) and \(b \geq c\) then \(b = b - 1\),
if \(c < b\) and \(b \geq a\) then \(b = b - 1\),
if \(c \leq b - 2\) then \(b = b - 1\).

3. Repeat

4. Repeat steps 1 and 2 for directions west-east (WE) direction, west-north to south-east (WN-SE) and north-east to west-south direction (NE to WS) (see Fig. 2-1a).

FIGURE 2-1 [here]

2.4.14 Homomorphic Filtering (homo)

The homo filter performs homomorphic filtering for image enhancement, by calculating the Fast Fourier Transform (FFT) of the logarithmic compressed image, applying a denoising homomorphic filter function \(H(.)\), and then performing the inverse FFT of the image \([18],\) \([19]\). The homomorphic filter function \(H(.)\), maybe constructed either using a band-pass Butterworth or a high-boost Butterworth filter. In this study, a high-boost Butterworth filter was used with the homomorphic function \([18]\):

\[
H_{u,v} = \gamma_L + \frac{\gamma_H}{1 + (D_0/D_{u,v})^2} \tag{2.11a}
\]

with

\[
D_{u,v} = \sqrt{(u - N/2)^2 + (v - N/2)^2} \tag{2.11b}
\]

where \(D_0 = 1.8\), is the cut of frequency of the filter, and \(\gamma_L = 0.4\), \(\gamma_H = 0.6\), are the gains for the low and high frequencies respectively, \(u\), \(v\), are the spatial coordinates of the frequency transformed image, and \(N\) the dimensions of the image in the \(u\), \(v\), space.
This form of filtering sharpens features and flattens speckle variations in an image.

### 2.4.15 Diffusion Filtering

Diffusion filters remove noise from an image by modifying the image via solving a partial differential equation (PDE). The smoothing is carried out depending on the image edges and their directions. Anisotropic diffusion is an efficient nonlinear technique for simultaneously performing contrast enhancement and noise reduction. It smoothes homogeneous image regions but retains image edges [5], [23], [24] without requiring any information from the image power spectrum. It may thus directly be applied to logarithmic compressed images.

Consider applying the isotropic diffusion equation given by \( \frac{dg_{i,j,t}}{dt} = \text{div}(d\nabla g) \) using the original noisy image, \( g_{i,j,t=0} \), as the initial condition, where \( g_{i,j,t=0} \) is an image in the continuous domain, \( i, j \), specifies spatial position, \( t \), is an artificial time parameter, \( d \), is the diffusion constant, and \( \nabla g \), is the image gradient. Modifying the image according to this linear isotropic diffusion equation is equivalent to filtering the image with a Gaussian filter. In this Section we will present conventional anisotropic diffusion (\( \text{ad} \)) and coherent nonlinear anisotropic diffusion (\( \text{nldif} \)).

#### 2.4.15.1 Anisotropic Diffusion Filtering (ad)

Perona and Malik [24] replaced the classical isotropic diffusion equation, as described above, by the introduction of a function, \( d_{i,j,t} = f(\nabla g) \), that smoothes the original image while trying to preserve brightness discontinuities with:

\[
\frac{dg_{i,j,t}}{dt} = \text{div}[d_{i,j,t} \nabla g_{i,j,t}] = \left[ \frac{d}{di} d_{i,j,t} \frac{d}{di} g_{i,j,t} \right] + \left[ \frac{d}{dj} d_{i,j,t} \frac{d}{dj} g_{i,j,t} \right]
\]

where \( |\nabla g| \) is the gradient magnitude, and \( d(|\nabla g|) \), is an edge stopping function, which is chosen to satisfy \( d \to 0 \) when \( |\nabla g| \to \infty \) so that the diffusion is stopped across edges. This
function, called the diffusion coefficient, \( d(\|\nabla g\|) \), which is a monotonically decreasing function of the gradient magnitude, \( \|\nabla g\| \), yields intra-region smoothing not inter-region smoothing [20], [21], [23], [24] by impeding diffusion at image edges. It increases smoothing parallel to the edge and stops smoothing perpendicular to the edge, as the highest gradient values are perpendicular to the edge and dilated across edges. The choice of \( d(\|\nabla g\|) \), can greatly affect the extent to which discontinuities are preserved. For example if \( d(\|\nabla g\|) \), is constant at all locations, then smoothing progresses in an isotropic manner. If \( d(\|\nabla g\|) \), is allowed to vary according to the local image gradient, then we have anisotropic diffusion. A basic anisotropic PDE is given in (12 a). Two different diffusion coefficients were proposed in [24] and also derived in [23]. The diffusion coefficient suggested were:

\[
d(\|\nabla g\|) = \frac{1}{1 + \left(\|\nabla g_{i,j}\|/K\right)^{2}},
\]

where \( K \), in (12 b) is a positive gradient threshold parameter, known as diffusion or flow constant [23]. In our study the diffusion coefficient in (12 b) was used as it was found to perform better in our images of carotid artery.

A discrete formulation of the anisotropic diffusion in (12 a) is [2], [23], [24]:

\[
\frac{dg_{i,j}}{dt} = \frac{\lambda}{\eta} \left[ d_{i+1,j}[g_{i+1,j} - g_{i,j}] + d_{i-1,j}[g_{i-1,j} - g_{i,j}] + d_{i,j+1}[g_{i,j+1} - g_{i,j}] + d_{i,j-1}[g_{i,j-1} - g_{i,j}] \right],
\]

where the new pixel gray value, \( f_{i,j} \), at location \( i, j \), is:

\[
f_{i,j} = g_{i,j} + \frac{1}{4} \frac{dg_{i,j}}{dt},
\]

where \( d_{i+1,j}, d_{i-1,j}, d_{i,j+1}, \) and \( d_{i,j-1} \), are the diffusion coefficients for the west, east, north and south pixel directions, in a four pixel neighborhood, around the pixel \( i, j \), where diffusion is computed respectively. The coefficient of variation leads to the largest diffusion where the
nearest-neighbor difference is largest (largest edge), while the smallest diffusion is calculated where the nearest-neighbor difference is smallest (the weakest edge). The constant, \( \lambda \in \mathbb{R}^+ \), is a scalar that determines the rate of diffusion, \( \eta_i \), represents the spatial neighborhood of pixel, \( i, j \), and \( |\eta_i| \), is the number of neighbors (usually four except at the image boundaries).

Perona and Malik [24] linearly approximated the directional derivative in a particular direction as, \( \nabla g_{i,j} = g_{i+1,j} - g_{i,j} \), (for the east direction of the central pixel \( i, j \)). Modifying the image according to the above equation in (13), which is a linear isotropic diffusion equation, is equivalent to filtering the image with a Gaussian filter. The parameters for the anisotropic diffusion filter used in this study were, \( \lambda = 0.25 \), \( \eta_i = 8 \), and the parameter \( K = 30 \), which was used for the calculation of the edge stopping function \( d(|\nabla g|) \), in (12b).

### 2.4.15.2 Coherent Nonlinear Anisotropic Diffusion Filtering (nldif)

The applicability of the \( ad \) filter (12) is restricted to smoothing with edge enhancement, where \( |\nabla g| \), has higher magnitude at edges. In general, the function \( d(|\nabla g|) \), in (12) can be put into a tensor form that measures local coherence of structures such that the diffusion process becomes more directional in both the gradient and the contour directions, which represent the directions of maximum and minimum variations, respectively. Therefore, the \( nldif \) filter will take the form:

\[
\frac{dg_{i,j,t}}{dt} = div[D\nabla g]
\]

(2.14)

where \( D \in \mathbb{R}^{2x2} \), is a symmetric positive semi-definite diffusion tensor representing the required diffusion in both gradient and contour directions and, hence, enhancing coherent structures as well as edges. The design of \( D \), as well as the derivation of the coherent nonlinear anisotropic diffusion model may be found in [25] and is given as:
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\[ D = (\omega_1 \omega_2) \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} \begin{pmatrix} \omega_1^T \\ \omega_2^T \end{pmatrix} \]  \hspace{1cm} (2.14a)

with

\[ \lambda_1 = \begin{cases} \alpha \left(1 - \frac{(\mu_1 - \mu_2)^2}{s^2}\right) & \text{if } (\lambda_1 - \lambda_2)^2 \leq s^2 \\ 0, & \text{else} \end{cases} \] \hspace{1cm} (2.14b)

\[ \lambda_2 = \alpha. \]

where the eigenvectors \( \omega_1, \omega_2 \) and the eigenvalues \( \lambda_1, \lambda_2 \) correspond to the directions of maximum and minimum variations and the strength of these variations, respectively. The flow at each point is affected by the local coherence, which is measured by \( (\mu_1 - \mu_2) \) in (14b).

The parameters used in this study for the \textit{nldif} filter were, \( s^2 = 2 \), and \( \alpha = 0.9 \), which were used for the calculation of the diffusion tensor \( D \), and the parameter step size \( m = 0.2 \), which defined the number of diffusion steps performed. The local coherence is close to zero in very noisy regions and diffusion must become isotropic \( (\mu_1 = \mu_2 = \alpha = 0.9) \), whereas in regions with lower speckle noise the local coherence must correspond to \( (\mu_1 - \mu_2)^2 > s^2 \) [25].

2.4.16 Wavelet Filtering (\textit{waveltc})

Speckle reduction filtering in the wavelet domain, used in this study, is based on the idea of the Daubenchies Symlet wavelet and on soft-thresholding denoising. It was first proposed by Donoho [30] and also investigated by [26], [27], [40]. The Symmlets family of wavelets, although not perfectly symmetrical, were designed to have the least asymmetry and highest number of vanishing moments for a given compact support [30]. The \textit{waveltc} filter, implemented in this study is described as follows:

1. Estimate the variance of the speckle noise, \( \sigma_n^2 \), from the logarithmic transformed noisy image, with (8).
2. Compute the discrete wavelet transform (DWT), using the Symlet wavelet for two scales.

3. For each sub-band

   Compute a threshold [28], [30]

   \[
   T = \begin{cases} 
   (T_{\text{max}} - \alpha(j - 1))\sigma_n & \text{if } T_{\text{max}} - \alpha(j - 1) > T_{\text{min}} \\
   T_{\text{min}}\sigma_n, & \text{else}
   \end{cases}
   \tag{2.15}
   \]

   where \( \alpha \), is a decreasing factor between two consecutive levels, \( T_{\text{max}} \), is a maximum factor for \( \sigma_n \), while \( T_{\text{min}} \), is a minimum factor. The threshold \( T \), is primarily calculated using, \( \sigma_n \), and a decreasing factor, \( T_{\text{max}} - \alpha(j - 1) \).

   Apply the thresholding procedure in a. on the wavelet coefficients in (ii).

4. Invert the multiscale decomposition to reconstruct the despeckled image, \( f \).

2.3 METHODOLOGY

2.4.1 Material

A total of 440 ultrasound images of the carotid artery bifurcation, 220 asymptomatic and 220 symptomatic were investigated in this study. Asymptomatic images were recorded from patients at risk of atherosclerosis in the absence of clinical symptoms, whereas symptomatic images were recorded from patients at risk of atherosclerosis, which have already developed clinical symptoms, such as a stroke episode.

2.4.2 Recording of ultrasound images

In this study ultrasound images of the carotid artery bifurcation were acquired using the ATL HDI-3000 ultrasound scanner. The ATL HDI-3000 ultrasound scanner is equipped with 64 elements fine pitch high-resolution, 38 mm broadband array, a multi element ultrasound scan head with an operating frequency range of 4-7 MHz, an acoustic aperture of 10x8 mm and a
transmission focal range of 0.8-11 cm [41]. In this work all images were recorded as they are displayed in the ultrasound monitor, after logarithmic compression. The images were recorded digitally on a magneto optical drive, with a resolution of 768x756 pixels with 256 gray levels. The image resolution was 16.66 pixels/mm.

2.4.3 Despeckle filtering

Ten despeckle filters were investigated as presented in Section 2.2, and were applied on the 440 logarithmically compressed ultrasound images.

2.4.4 Texture analysis

Texture provides useful information for the characterization of atherosclerotic plaque [42]. In this study a total of 56 different texture features were extracted both from the original and the despeckled images as follows [42], [43]:

2.4.4.1 Statistical Features (SF)

1. Mean,
2. Median
3. Variance ($\sigma^2$)
4. Skewness ($\sigma^3$)
5. Kurtosis ($\sigma^4$), and
6. Speckle index ($\sigma / m$).

2.4.4.2 Spatial Gray Level Dependence Matrices (SGLDM)

SGLDM as proposed by Haralick et al. [43]:

1. Angular second moment,
2. Contrast,
3. Correlation,
4. Sum of squares: variance,
5. Inverse difference moment,
6. Sum average,
7. Sum variance,
8. Sum entropy,
9. Entropy,
10. Difference variance,
11. Difference entropy, and
12. Information measures of correlation.

Each feature was computed using a distance of one pixel. Also for each feature the mean values and the range of values were computed, and were used as two different feature sets.

2.4.4.3 Gray Level Difference Statistics (GLDS) [44]:
1. Contrast,
2. Angular second moment,
3. Entropy, and
4. Mean.

2.4.4.4 Neighbourhood Gray Tone Difference Matrix (NGTDM) [45]:
1. Coarseness,
2. Contrast,
3. Business,
4. Complexity, and
5. Strength.

2.4.4.5 Statistical Feature Matrix (SFM) [46]:
1. Coarseness
2. Contrast

3. Periodicity, and

4. Roughness.

2.4.4.6 Laws Texture Energy Measures (TEM) [46]

For the laws TEM extraction, vectors of length \( l = 7, \; L = (1,6,15,20,15,6,1), \)

\( E = (-1,-4,-5,0,5,4,1) \) and \( S = (-1,-2,1,4,1-2,-1) \) were used, where \( L \) performs local

averaging, \( E \) acts as an edge detector and \( S \) acts as a spot detector. The following TEM

features were extracted:

1. LL - texture energy (TE) from LL kernel

2. EE - TE from EE kernel

3. SS - TE from SS kernel

4. LE - average TE from LE and EL kernels

5. ES - average TE from ES and SE kernels, and

6. LS - average TE from LS and SL kernels.

2.4.4.7 Fractal Dimension Texture Analysis (FDTA) [46]

Hurst coefficient, \( H^{(k)} \), for resolutions \( k=1, \; 2, \; 3, \; 4. \)

2.4.4.8 Fourier Power Spectrum (FPS) [46]:

1. Radial sum, and

2. Angular sum.

2.4.5 Distance measures

In order to identify the most discriminant features separating asymptomatic and symptomatic

ultrasound images, before and after despeckle filtering the following distance measure was

computed for each feature [42]:

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\[
d_{zf} = \left| m_{za} - m_{zs} \right| \sqrt{\frac{\sigma_{za}^2 + \sigma_{zs}^2}{2}} \tag{2.16}
\]

where \( z \) is the feature index, \( c \) if \( o \) indicates the original image set and if \( f \) indicates the despeckled image set, \( m_{za} \) and \( m_{zs} \) are the mean values and \( \sigma_{za} \) and \( \sigma_{zs} \) are the standard deviations of the asymptomatic and symptomatic classes respectively. The most discriminant features are the ones with the highest distance values [42]. If the distance after despeckle filtering is increased i.e.:

\[
d_{zf} > d_{zo} \tag{2.17}
\]

then it can be derived that the classes may be better separated.

For each feature, a percentage distance was computed as:

\[
\text{feat}_z \_ \text{dis} = (d_{zf} - d_{zo})100. \tag{2.18}
\]

For each feature set, a score distance was computed as:

\[
\text{Score}_z \_ \text{Dis} = (1/N) \sum_{z=1}^{N} (d_{zf} - d_{zo})100 \tag{2.19}
\]

where \( N \) is the number of features in the feature set. It should be noted that for all features a larger feature distance shows improvement.

2.4.6 Univariate statistical analysis

The Wilcoxon rank sum test was used in order to detect if for each texture feature a significant (S) difference or not (NS) exists between the original and the despeckled images at \( p<0.05 \).

2.4.7 kNN Classifier

The statistical k-nearest-neighbour (kNN) classifier using the Euclidean distance with \( k=7 \) was also used to classify a plaque image as asymptomatic or symptomatic [42]. The leave-one-out method was used for evaluating the performance of the classifier, where each case is
evaluated in relation to the rest of the cases. This procedure is characterized by no bias concerning the possible training and evaluation bootstrap sets. The kNN classifier was chosen because it is simple to implement and computationally very efficient. This is highly desired due to the many feature sets and filters tested [46].

2.4.8 Image quality evaluation metrics

Differences between the original, \( g_{i,j} \), and the despeckled, \( f_{i,j} \), images were evaluated using the image quality evaluation metrics presented in Chapter 1.2.6 and in [48].

2.4.9 Visual evaluation by experts

Visual evaluation can be broadly categorized as the ability of an expert to extract useful anatomical information from an ultrasound image. The visual evaluation varies of course from expert to expert and is subject to the observer’s variability [55]. The visual evaluation, in this study, was carried out according to the ITU-R recommendations with the Double Stimulus Continuous Quality Scale (DSCQS) procedure [51]. A total of 100 ultrasound images of the carotid artery bifurcation (50 asymptomatic and 50 symptomatic) were evaluated visually by two vascular experts, a cardiovascular surgeon, and a neurovascular specialist before and after despeckle filtering. For each case, the original and the despeckled images (despeckled with filters \( ls mv, ls msc, median, w iener, h omog, g f 4 d, h om o, a d, n ld i f, a nd w a v e ltc \)) were presented without labelling at random to the two experts. The experts were asked to assign a score in the one to five scale corresponding to low and high subjective visual perception criteria. Five was given to an image with the best visual perception. Therefore the maximum score for a filter is 500, if the expert assigned the score of five for all the 100 images. For each filter, the score was divided by five to be expressed in percentage format. The experts were allowed to give equal scores to more than one image in each case. For each class and for each filter the average score was computed.
The two vascular experts evaluated the area around the distal common carotid, 2-3 cm before the bifurcation and the bifurcation. It is known that measurements taken from the far wall of the carotid artery are more accurate than those taken from the near wall [56]. Furthermore, the experts were examining the image in the lumen area, in order to identify the existence of a plaque or not.

2.4 RESULTS

In this Section we present the results of the 10 despeckle filters described in Section II, applied on 220 asymptomatic and 220 symptomatic ultrasound images of the carotid artery bifurcation. A total of 56 texture features were computed and the most discriminant ones are presented. Furthermore the performance of these filters is investigated for discriminating between asymptomatic and symptomatic images using the statistical kNN classifier. Moreover, nine different image quality evaluation metrics were computed, as well as visual evaluation scores carried out by two experts.

2.4.1 Evaluation of despeckle filtering on a symptomatic ultrasound image

Figure 2-2 shows an ultrasound image of the carotid together with the despeckled images. The best visual results as assessed by the two experts were obtained by the filters lsmv and lsminsc, whereas the filters gf4d, ad, and nl2dif also showed good visual results but smoothed the image considerably and thus edges and subtle details may be lost. Filters that showed a blurring effect are the median, wiener, homog, and waveltc. Filters wiener, homog, and waveltc showed poorer visual results.

FIGURE 2-2 [here]
2.4.2 Texture analysis: Distance measures, Table 2-2

Despeckle filtering and texture analysis were carried out on 440 ultrasound images of the carotid. Table 2-2 tabulates the results of \(\text{feat}_\text{dis}\), (18), and \(\text{Score}_\text{Dis}\) (19), for SF, SGLDM range of values and NGTDM feature sets for the 10 despeckle filters. The results of these feature sets are presented only, since were the ones with the best performance. The filters are categorized in local statistics, median, maximum homogeneity (HF), geometric (GF), homomorphic (HM), diffusion and wavelet filters, as introduced in Sections I and II. Also the number of iterations (Nr. of It.) for each filter is given, which was selected based on C and on the visual evaluation of the two experts. When C was minimally changing then the filtering process was stopped. The bolded values represent the values that showed an improvement after despeckle filtering compared to the original. The last row in each sub-table shows the \(\text{Score}_\text{Dis}\) for all features, where the highest value indicates the best filter in the sub-table. Additionally, a total score distance \(\text{Score}_\text{Dis}_T\) was computed for all feature sets shown in the last row of Table 2-2. Some of the despeckle filters, shown in Table 2-2, are changing a number of texture features, by increasing the distance between the two classes, (positive values in Table 2-2), and therefore making the identification and separation between asymptomatic and symptomatic plaques more feasible. A positive feature distance shows improvement after despeckle filtering, whereas a negative shows deterioration.

In the first part of Table 2-2 the results of the SF features are presented, where the best \(\text{Score}_\text{Dis}\) is given for the filter \text{homo} followed by the \text{lsminsc, lsmv, homog, nldif, waveltc, median, and wiener}, with the worst \(\text{Score}_\text{Dis}\) given by \text{gf4d}. All filters reduced the speckle index, C. Almost all filters reduced significantly the variance, \(\sigma^2\), and the kurtosis, \(\sigma^3\), of the histogram, as it may be seen from the bolded values in the first part of Table 2-2.

In the second part of the Table 2-2 the results of the SGLDM-Range of values features set are tabulated. The filters with the highest \(\text{Score}_\text{Dis}\) in the SGLDM range of values features set,
are homo, lsminsc, median, ad, and homog, whereas all other the filters (nldif, wiener, waveltc, gf4d, lsmv) are presenting a negative Score Dis. Texture features, which improved in most of the filters, are the contrast, correlation, sum of squares variance, sum average, and sum variance.

In the third part of Table 2-2, for the NGTDM feature set almost all filters showed an improvement in Score Dis. Best filters in the NGTDM feature set were, the homo, lsminsc, homog, and lsmv. Texture features improved at most were the completion, coarseness and contrast. The completion of the image was increased by all filters.

Finally, in the last row of Table 2-2, the total score distance, Score Dis T, for all feature sets is shown, where best values were obtained by the filters homo, lsminsc, median, lsmv, homog, and ad.

TABLE 2-2 [here]

2.4.3 Texture analysis: Univariate statistical analysis, Table 2-3

Table 2-3 shows the results of the rank sum test, which was performed on the SGLDM range of values features set of Table 2-2, for the 10 despeckle filters. The test was performed to check if significant differences exist between the features computed on the 440 original and the 440 despeckled images. Filters that resulted with the most significant number of features after despeckle filtering as shown with the score row of Table 2-3 were the following: lsmv, gf4d, lsminsc and nldif. The rest of the filters gave a lower number of significantly different features. Features that showed a significant difference after filtering were the inverse difference moment, IDM, angular second moment, ASM, sum of entropy, contrast, correlation, sum of squares variance, SOSV, and sum variance, \( \sum Var \). These features were mostly affected after despeckle filtering and they were significantly different.

TABLE 2-3 [here]
2.4.4 Texture analysis: kNN Classifier, Table 2-4

Table 2-4 shows the percentage of correct classifications score for the kNN classifier with k=7 for classifying a subject as asymptomatic or symptomatic. The classifier was evaluated using the leave one out method [46], on 220 asymptomatic, and 220 symptomatic images on the original, and despeckled images. The percentage of correct classifications score is given for the following feature sets: Statistical Features, SF, Spatial Gray Level Dependence Matrix Mean Values, SGLDMm, Spatial Gray Level Dependence Matrix Range of Values, SGLDMr, Gray Level Difference Statistics, GLDS, Neighborhood Gray Tone Difference Matrix, NGTDM, Statistical Feature Matrix, SFM, Laws Texture Energy Measures, TEM, Fractal Dimension Texture Analysis, FDTA, and Fourier Power Spectrum, FPS. Filters that showed an improvement in classifications success score compared to that of the original image set, were in average (last row of Table 2-4) the filter homo (3 %), gf4d (1%), and lsminsc (1%).

TABLE 2-4 [here]

Feature sets, which benefited mostly by the despeckle filtering were the SF, GLDS, NGTDM, and TEM when counting the number of cases that the correct classifications score was improved. Less improvement was observed, for the feature sets FDTA, SFM, SGLDMm, FPS and SGLDMr. For the feature set SGLDMr better results are given for the lsminsc filter with an improvement of 2%. This is the only filter that showed an improvement for this class of features. For the feature set TEM the filter lsmv shows the best improvement with 9%, whereas for the FPS feature set the filter lsminsc gave the best improvement with 5%. The filter lsminsc showed improvement in the GLDS and NGTDM feature sets, whereas the filter lsmv showed improvement for the feature sets SF and TEM.
2.4.5 Image quality evaluation metrics, Table 2-5

Table 2-5 tabulates the image quality evaluation metrics presented in Section III.H, for the 220 asymptomatic and 220 symptomatic ultrasound images between the original and the despeckled images respectively. Best values were obtained for the \textit{nldif}, \textit{lsmv} and \textit{waveltc} with lower MSE, RMSE, Err3, and Err4 and higher SNR and PSNR. The GAE was 0.00 for all cases, and this can be attributed to the fact that the information between the original and the despeckled images remains unchanged. Best values for the universal quality index, \textit{Q}, and the structural similarity index, \textit{SSIN} were obtained for the filters \textit{lsmv} and \textit{nldif}.

TABLE 2-5 [here]

2.4.6 Visual evaluation by experts, Table 2-6

Table 2-6 shows the results of the visual evaluation of the original and despeckled images made by two experts, a cardiovascular surgeon and a neurovascular specialist. The last row of Table 2-6 presents the overall average percentage (%) score assigned by both experts for each filter.

TABLE 2-6 [here]

For the cardiovascular surgeon, the average score, showed that the best despeckle filter is the \textit{lsmv} with a score of 62\%, followed by \textit{gf4d}, \textit{median}, \textit{homog} and \textit{original} with scores of 52\%, 50\%, 45\% and 41\% respectively. For the neurovascular specialist, the average score showed that the best filter is the \textit{gf4d} with a score of 72\%, followed by \textit{lsmv}, \textit{original}, \textit{lsminsc} and \textit{median} with scores of 71\%, 68\%, 68\% and 66\% respectively. The overall average % score shows that the highest score was given to the filter \textit{lsmv} (67\%), followed by \textit{gf4d} (62\%), \textit{median} (58\%), and \textit{original} (54\%). It should be emphasized that the despeckle filter \textit{lsmv} is the only filter that was graded with a higher score than the original by both experts for the asymptomatic and symptomatic image sets.
We may observe a difference in the scorings between the two vascular specialists and this is because, the cardiovascular surgeon is primarily interested in the plaque composition and texture evaluation whereas the neurovascular specialist is interested to evaluate the degree of stenosis and the lumen diameter in order to identify the plaque contour. Filters *lsmv* and *gf4d* were identified as the best despeckle filters, by both specialists as they improved visual perception with overall average scores of 67% and 62% respectively. The filters *waveltc* and *homo* were scored by both specialists with the lowest overall average scores of 28% and 29% respectively.

By examining the visual results of Fig. 2-2, the statistical results of Table 2-2 to Table 2-5 and the visual evaluation of Table 2-6 we can conclude that the best filters are *lsmv* and *gf4d*, which may be used for both plaque composition enhancement and plaque texture analysis, whereas the filters *lsmv*, *gf4d* and *lsminsc* are more appropriate to identify the degree of stenosis and therefore may be used when the primary interest is to outline the plaque borders.

### 2.5 DISCUSSION

Despeckle filtering is an important operation in the enhancement of ultrasound images of the carotid artery, both in the case of texture analysis, and in the case of image quality evaluation and visual evaluation by the experts. In this study a total of 10 despeckle filters were comparatively evaluated on 440 ultrasound images of the carotid artery bifurcation, and the validation results are summarised in Table 2-7.

As given in Table 2-7, filters *lsmv*, *lsminsc*, and *homo*, improved the class separation between the asymptomatic and the symptomatic classes (see also Table 2-2). Filters *lsmv*, *lsminsc*, and *gf4d* gave a high number of significantly different features (see Table 2-3). Filters *lsminsc*, *gf4d*, and *homo*, gave only a marginal improvement in the percentage of correct classifications success rate (see Table 2-4). Moreover, filters *lsmv*, *nldif*, and *waveltc*, gave better image quality evaluation results (see Table 2-5). Filters *lsmv*, and *gf4d*, improved the visual
assessment carried out by the experts (see Table 2-6). It is clearly shown that filter \textit{lsmv} gave the best performance, followed by filters \textit{lsminsc}, and \textit{gf4d} (see Table 2-7). Filter \textit{lsmv} or \textit{gf4d} can be used for despeckling asymptomatic images where the expert is interested mainly in the plaque composition and texture analysis. Filters \textit{lsmv} or \textit{gf4d} or \textit{lsminsc} can be used for despeckling of symptomatic images where the expert is interested in identifying the degree of stenosis and the plaque borders. Filters \textit{homo}, \textit{nldif}, and \textit{waveltc} gave poorer performance.

Filter \textit{lsmv} gave very good performance, with respect to: (i) preserving the mean and the median as well as decreasing the variance and the speckle index of the image, (ii) increasing the distance of the texture features between the asymptomatic and the symptomatic classes, (iii) significantly changing the SGLDM range of values texture features after filtering based on the Wilcoxon rank sum test, (iv) marginally improving the classification success rate of the kNN classifier for the classification of asymptomatic and symptomatic images in the cases of SF, SMF and TEM feature sets, and (v) improving the image quality of the image. The \textit{lsmv} filter, which is a simple filter, is based on local image statistics. It was first introduced in [15], [10], [16] by Jong-Sen Lee and co-workers and it was tested on a few SAR images with satisfactory results. It was also used for SAR imaging in [14] and image restoration in [17], again with satisfactory results.

\textbf{TABLE 2-8 [here]}

Filter \textit{lsminsc} gave the best performance with respect to: (i) preserving the mean, as well as decreasing the variance and the speckle index and increasing the contrast of the image, (ii) increasing the distance of the texture features between the asymptomatic and the symptomatic classes, (iii) significantly changing the SGLDM texture features after filtering based on the Wilcoxon rank sum test, (iv) improving the classification success rate of the kNN classifier for the classification of asymptomatic and symptomatic images in the cases of SF, SGLDMr, GLDS, NGTDM, FDTA and FPS feature sets. Filter \textit{lsminsc} was originally introduced by
Nagao in [34] and was tested on an artificial and a SAR image with satisfactory performance. In this study the filter was modified, by using the speckle index instead of the variance value for each sub window (as described in Section II.A.2, equation (9)).

Filter $gf4d$ gave very good performance with respect to: (i) decreasing the speckle index, (ii) marginally increasing the distance of the texture features between the asymptomatic and the symptomatic classes, (iii) significantly changing the SGLDM range of values texture features after filtering based on the Wilcoxon rank sum test, (iv) improving the classification success rate of the kNN classifier for the classification of asymptomatic and symptomatic images in the cases of SGLDMm, GLDS, NGTDM, SFM and TEM feature sets. The geometric filter $gf4d$ was introduced by Crimmins [11], and was tested visually on a few SAR images with satisfactory results.

Filters used for speckle reduction in ultrasound imaging by other investigators include: median [35], wiener [14], homog [8], homo [18], [19], ad [5], and waveltc [30], [57]. However, these filters were evaluated on a small number of images, and their performance was tested based only on the mean, median, standard deviation and speckle index of the image before and after filtering.

The median and the wiener filters were originally used by many researchers for suppressing the additive and later for suppressing the multiplicative noise in different types of images [2]-[10], [14], [35]. The results of this study showed that the wiener and median filters were not able to remove the speckle noise and produced blurred edges in the filtered image (see Fig. 2-2). In this study the median filter performed poorer as shown in Tables 2-2 and 2-3, and 2-4. The homog [8] and homo [2], [18], [19] filters, were recently used by some researchers for speckle reduction but our results in Tables 2-2, 2-3, and 2-5 and the visual evaluation of the experts in Table 2-6 showed poor performance especially for the homo filter.
Anisotropic diffusion is an efficient nonlinear technique for simultaneously performing contrast enhancement and noise reduction. It smooths homogeneous image regions but retains image edges [24]. Anisotropic diffusion filters usually require many iteration steps compared with the local statistic filters. In a recent study [5], speckle reducing anisotropic diffusion filtering was proposed as the most appropriate filter for ultrasound images of the carotid artery. However, in this study, $ad$, as shown in Tables 2-2, 2-3, 2-4, 2-5 and 2-6 performed poorer compared to $lsmv$, $gf4d$ and $lsminsc$.

Furthermore, wavelet filtering proposed by Donoho in [30], was investigated for suppressing the speckle noise in SAR images [16], [37], real world images [26] and ultrasound images [27] with favourable results. In this study, it is shown that the $waveltc$ filter gave poorer performance for removing the speckle noise from the ultrasound images of the carotid artery (Tables 2-2, 2-3).

Anisotropic diffusion and wavelet filtering were also investigated in [32] to carotid artery ultrasound images, where a simple pre-processing procedure based on spectrum equalisation and a non-linear shrinkage procedure was applied, in order to suppress the spiky component to the logarithmic transformed speckle and to modify the noise component to approximately white Gaussian. Then anisotropic diffusion and wavelet filtering, which are based on additive noise model were applied. The pre processing procedure, does not modify the structures of a specific filtering method, but rather alters the noise in such a way that it becomes very similar to white Gaussian, so that existing powerful methods for additive noise reduction may be applied. A wavelet multiscale normalised modulus-based wavelet diffusion method was also recently proposed in [57], which utilises the properties of the wavelet and the edge enhancement feature of the nonlinear diffusion. The performance of this algorithm was tested on cardiac ultrasound images and showed superior performance when compared to the speckle reducing anisotropic method [5]. In [60] the effect of despeckle filtering on lossy
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Compression was investigated, where compression and then despeckle filtering was applied on ultrasound images or a renal cell carcinoma. The images were simultaneously denoised and compressed in a single step and it was shown that the Laplacian distribution compression scheme performs better.

In conclusion, despeckle filtering is an important operation in the enhancement of ultrasonic imaging of the carotid artery. In this study it was shown that simple filters based on local statistics (lsmv and lsminsc) and geometric filtering (gf4d) could be used successfully for the processing of these images. In this context, despeckle filtering can be used as a pre-processing step for the automated segmentation of the IMT [58] and the carotid plaque, followed by the carotid plaque texture analysis, and classification. This field is currently being investigated by our group [59]. Initial findings show promising results, however, further work is required to evaluate the performance of the suggested despeckle filters at a larger scale as well as their impact in clinical practise. In addition, the usefulness of the proposed despeckle filters, in portable ultrasound systems and in wireless telemedicine systems still has to be investigated.

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| Speckle Reduction Technique | Investigator | Method | Filter Name |
|----------------------------|--------------|--------|-------------|
| Local Statistics           | [7]-[15], [14]-[17] | Moving window utilising local statistics | lsmv |
|                            | [7]-[15]     | a) mean (m), variance ($\sigma^2$) | lsmv |
|                            | [7]-[15]     | b) mean, variance, 3rd and 4th moments (higher moments) and entropy | lsmv |
|                            | [34]         | c) Homogeneous mask area filters | lsminsc |
|                            | [2]-[15], [16] | e) Wiener filtering | wiener |
| Median                     | [35]         | Median filtering | median |
| Homogeneity                | [8]          | Based on the most homogeneous neighbourhood around each pixel | homog |
| Geometric                  | [11]         | Non linear iterative algorithm | gfd |
| Homomorphic                | [2], [18], [19] | The image is logarithmically transformed, the Fast Fourier transform (FFT) is calculated, denoised, the inverse FFT is calculated and finally exponentially transformed back | homo |
| Anisotropic Diffusion      | [2], [5], [13], [14], [20], [21]-[24], [25] | Non-linear filtering technique for simultaneously performing contrast enhancement and noise reduction. Exponential damp kernel filters utilising diffusion | ad |
|                           |             | Coherence enhancing diffusion | nldif |
| Wavelet                    | [16], [26]-[29], [30], [37] | Only the useful wavelet coefficients are utilised | wavelet |
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| Feature | Local Statistics | HF | GF | HM | Diffusion | Wavelet |
|---------|------------------|----|----|----|-----------|---------|
|         | lsmv lsminc wiener homog gf4d homo ad nldif waveltc |     |    |    |           |         |
| Nr. of It. | 4 1 2 2 1 3 2 20 5 5 |     |    |    |           |         |

SF-Statistical Features

| Feature | Mean | Median | σ | C | Score_dis |
|---------|------|--------|---|---|------------|
|         | 14   | -5     | 18 | 0.4 | 27        |
|         | 22   | -17    | 38 | 0.3 | 45        |
|         | 19   | -26    | 18 | 0.3 | 9         |
|         | 4    | -5     | 7  | -0.1| 3         |
|         | 11   | -15    | 7  | -15 | 164       |
|         | 3    | -9     | 3  | -15 | 18        |
|         | 164  | 110    | 9  | 17  | 5         |
|         | 18   | -29    | 7  | 7   | 15        |
|         | 5    | -6     | 9  | 7   | 8         |
|         | 20   | -29    | 7  | 7   | 8         |
|         | 5    | -6     | 9  | 7   | 8         |
|         | 15   | -15    | 7  | 7   | 8         |

SGLDM Range of Values–Spatial Gray Level Dependence Matrix

| Feature | ASM | Contrast | Correlation | SOSV | IDM | SAV | Covar | ∑Var | Score_dis |
|---------|-----|----------|-------------|------|-----|-----|-------|-------|-----------|
|         | -21 | 47       | 12          | 9    | -50 | 17  | 19    | 17   | -1       |
|         | -0.5| 107      | 59          | 40   | -11 | 24  | 38    | 38   | -34      |
|         | -29 | 64       | 15          | 18   | -48 | 7   | 18    | 18   | -14      |
|         | 2   | -3       | -5          | 10   | 2   | 15  | 15    | 15   | -1       |
|         | -4  | 165      | 2           | 16   | -2  | 169 | 3     | 3     | 22       |
|         | -8  | 104      | 10          | 10   | 2   | 26  | 16    | 16   | 6        |
|         | -47 | 13       | -5          | 9    | 8   | 15  | -2    | -2    | 22       |
|         | -25 | 22       | 50          | 101  | 9   | 8   | 16    | 16   | 8        |
|         | -17 | 104      | 54          | 16   | 9   | 26  | -2    | -2    | 22       |
|         | -20 | 13       | 54          | 101  | 8   | 15  | 16    | 16   | 8        |

NGTDM–Neighbourhood Gray Tone Difference Matrix

| Feature | Coarseness | Contrast | Busyness | Completion | Score_dis | Score _dis − T |
|---------|------------|----------|----------|------------|-----------|----------------|
|         | 30         | 7        | 17       | 64         | 118       | 144           |
|         | 87         | -0.3     | 26       | 151        | 264       | 551           |
|         | 4          | 9        | -30      | 21         | -14       | -14           |
|         | 9          | 8        | 8        | 53         | 78        | 208           |
|         | -16        | 0.4      | 1        | 80         | -13       | 208           |
|         | -7         | -4       | -1        | 2          | -37       | 108           |
|         | 72         | -4       | 48        | 150        | 137       | 108           |
|         | -36        | -4       | -14       | 63         | 184       | 108           |
|         | -37        | -3       | -14       | 18         | 222       | 108           |
|         | -33        | -3       | -14       | 27         | 222       | 108           |

ASM: Angular 2nd moment, SOSV: Sum of squares variance, IDM: Inverse difference moment, SAV: Sum average, ∑Var: Sum Variance

HF: Homogeneity, GF: Geometric, HM: Homomorphic

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Table 2-3
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| Feature   | Local Statistics | Median | HF | GF | HM | Diffusion | Wavelet | Score |
|-----------|------------------|--------|----|----|----|-----------|---------|-------|
| ASM       | S                | S      | NS | NS | NS | S         | S       | S     | 7     |
| Contrast  | S                | NS     | NS | NS | NS | S         | NS      | S     | 3     |
| Correlation| S               | S      | NS | NS | NS | S         | NS      | S     | 3     |
| SOSV      | S                | NS     | NS | NS | NS | S         | NS      | NS    | 2     |
| IDM       | S                | S      | NS | NS | NS | S         | NS      | S     | 8     |
| SAV       | NS               | NS     | NS | NS | NS | S         | NS      | NS    | 0     |
| $\sum \text{Var}$ | S       | S      | NS | NS | NS | S         | NS      | S     | 2     |
| $\sum \text{Entropy}$ | S     | S      | NS | NS | NS | S         | NS      | S     | 5     |
| Score     | 7                | 5      | 0  | 1  | 2  | 6         | 1       | 1     | 4     | 3     |

ASM: Angular 2nd moment, SOSV: Sum of squares variance, IDM: Inverse difference moment, SAV: Sum average, $\sum \text{Var}$ : Sum Variance

HM: Homomorphic, HF: Homogeneity, GF: Geometric, HM: Homomorphic. Score: illustrates the number of S
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Percentage Of Correct Classifications Score For The kNN Classifier With k=7 For The Original And The Filtered Image Sets. Bolded Values Indicate Improvement After Despeckling. C.P. Loizou et al., Comparative Evaluation of Despeckle Filtering in Ultrasound Imaging of the Carotid Artery, IEEE Trans. Ultrasonics Ferroelectrics and Frequency Control, vol. 52, no. 10, pp. 1653-1669, 2005, © 2005 IEEE.

| Feature set | No. of Feat. | original lsmv | lsmv | wiener | median lsmv | median | homog | gf4d | homo | ad | nldif | wavelet |
|-------------|--------------|----------------|------|--------|-------------|--------|-------|------|------|----|-------|---------|
| SF          | 5            | 59             | 62   | 61     | 61          | 57     | 63    | 59   | 65   | 60 | 52    | 61      |
| SGLDMm      | 13           | 65             | 63   | 64     | 62          | 63     | 69    | 67   | 68   | 61 | 66    | 63      |
| SGLDMr      | 13           | 70             | 66   | 72     | 64          | 66     | 65    | 70   | 69   | 64 | 65    | 65      |
| GLDS        | 4            | 64             | 63   | 66     | 61          | 69     | 64    | 66   | 72   | 59 | 58    | 62      |
| NGTDM       | 5            | 64             | 63   | 68     | 60          | 69     | 63    | 65   | 57   | 60 | 61    | 62      |
| SFM         | 4            | 62             | 62   | 60     | 62          | 58     | 55    | 65   | 68   | 59 | 56    | 55      |
| TEM         | 6            | 59             | 68   | 52     | 60          | 59     | 66    | 60   | 65   | 53 | 60    | 60      |
| FDTA        | 4            | 64             | 63   | 66     | 53          | 68     | 53    | 62   | 73   | 55 | 54    | 62      |
| FPS         | 2            | 59             | 54   | 64     | 59          | 58     | 59    | 59   | 59   | 52 | 48    | 55      |
| Average     |              | 63             | 63   | 64     | 60          | 63     | 62    | 64   | 66   | 58 | 58    | 61      |

SF: Statistical Features, SGLDMm: Spatial Gray Level Dependence Matrix Mean Values, SGLDMr: Spatial Gray Level Dependence Matrix Range of Values, GLDS: Gray Level Difference Statistics, NGTDM: Neighborhood Gray Tone Difference Matrix, SFM: Statistical Feature Matrix, TEM: Laws Texture Energy Measures, FDTA: Fractal Dimension Texture Analysis, FPS: Fourier Power Spectrum.

HF: Homogeneity, GF: Geometric, HM: Homomorphic
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Image Quality Evaluation Metrics Computed For The 220 Asymptomatic And 220 Symptomatic Images. C.P. Loizou et al., Comparative Evaluation of Despeckle Filtering in Ultrasound Imaging of the Carotid Artery,” IEEE Trans. Ultrasonics Ferroelectrics and Frequency Control, vol. 52, no. 10, pp. 1653-1669, 2005, © 2005 IEEE.

| Feature set | Local Statistics | Median | HF | GF | HM | Diffusion | Wavelet |
|-------------|------------------|--------|----|----|----|-----------|---------|
|             | lsmv | lsminc | wiener | median | homog | gf4d | homo | ad | nldif | wavelet |
| Asymptomatic Images |          |        |      |     |     |       |    |    |    |        |
| MSE         | 13   | 86    | 19   | 131 | 42  | 182   | 758 | 132 | 8  | 11     |
| RMSE        | 3    | 9     | 4    | 10  | 6   | 13    | 27  | 11  | 2  | 3      |
| Err3        | 7    | 17    | 5    | 25  | 14  | 25    | 38  | 21  | 5  | 4      |
| Err4        | 11   | 26    | 7    | 41  | 24  | 40    | 49  | 32  | 10 | 5      |
| GAE         | 0    | 0     | 0    | 0   | 0   | 0     | 0   | 0   | 0  | 0      |
| SNR         | 25   | 17    | 23   | 16  | 21  | 14    | 5   | 14  | 28 | 25     |
| PSNR        | 39   | 29    | 36   | 29  | 34  | 27    | 20  | 28  | 41 | 39     |
| Q           | 0.83 | 0.78  | 0.74 | 0.84| 0.92| 0.77  | 0.28| 0.68| 0.93| 0.65   |
| SSIN        | 0.97 | 0.88  | 0.92 | 0.94| 0.97| 0.88  | 0.43| 0.87 | 0.97| 0.9    |
| Symptomatic Images |          |        |      |     |     |       |    |    |    |        |
| MSE         | 33   | 374   | 44   | 169 | 110 | 557   | 1452| 374 | 8  | 23     |
| RMSE        | 5    | 19    | 6    | 13  | 10  | 23    | 37  | 19  | 3  | 5      |
| Err3        | 10   | 33    | 9    | 25  | 20  | 43    | 51  | 31  | 5  | 6      |
| Err4        | 16   | 47    | 11   | 38  | 30  | 63    | 64  | 43  | 7  | 8      |
| GAE         | 0    | 0     | 0    | 0   | 0   | 0     | 0   | 0   | 0  | 0      |
| SNR         | 24   | 13    | 22   | 16  | 17  | 12    | 5   | 12  | 29 | 25     |
| PSNR        | 34   | 23    | 33   | 26  | 28  | 21    | 17  | 23  | 39 | 36     |
| Q           | 0.82 | 0.77  | 0.7  | 0.79| 0.87| 0.75  | 0.24| 0.63| 0.87| 0.49   |
| SSIN        | 0.97 | 0.85  | 0.89 | 0.81| 0.94| 0.85  | 0.28| 0.81| 0.97| 0.87   |

MSE: Mean square error, RMSE: Randomised mean square error, Err3, Err4: Minowski metrics, GAE: Geometric average error, SNR: Signal to noise radio, PSNR: Peak signal to noise radio, Q: universal quality index, SSIN: structural similarity index
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Table 2-6

Percentage Scoring Of Visual Evaluation Of The Original And Despeckled Images (50 Asymptomatic (A) And 50 Symptomatic (S)) By The Experts. C.P. Loizou et al., Comparative Evaluation of Despeckle Filtering in Ultrasound Imaging of the Carotid Artery," IEEE Trans. Ultrasonics Ferroelectrics and Frequency Control, vol. 52, no. 10, pp. 1653-1669, 2005, © 2005 IEEE.

| Experts            | A/S | Statistics | Local | Median | HF | GF | HM | Diffusion | Wavelet |
|--------------------|-----|------------|-------|--------|----|----|----|-----------|---------|
|                    |     | original   | lsme  | Lsminsc| median| homog| gfd | homo      | nlif     | waveltc |
| Cardiovascular A   | 33  | 75         | 33    | 43     | 47  | 61 | 19 | 43        | 32      |
| Surgeon S          | 48  | 49         | 18    | 57     | 43  | 42 | 20 | 33        | 22      |
| Average %          | 41  | 62         | 26    | 50     | 45  | 52 | 19 | 38        | 27      |
| Neurovascular A    | 70  | 76         | 73    | 74     | 63  | 79 | 23 | 52        | 29      |
| Specialist S       | 66  | 67         | 63    | 58     | 45  | 65 | 55 | 41        | 28      |
| Average %          | 68  | 71         | 68    | 66     | 54  | 72 | 39 | 47        | 28      |
| Overall Average %  | 54  | 67         | 47    | 58     | 50  | 62 | 29 | 43        | 28      |

HF: Homogeneity, GF: Geometric, HM: Homomorphic
Table 2-7
Summary Findings Of Despeckle Filtering In Ultrasound Imaging Of The Carotid Artery. C.P. Loizou et al., Comparative Evaluation of Despeckle Filtering in Ultrasound Imaging of the Carotid Artery, IEEE Trans. Ultrasonics Ferroelectrics and Frequency Control, vol. 52, no. 10, pp. 1653-1669, 2005, © 2005 IEEE.

| Despeckle Filter          | Statistical and Texture Features | Statistical Analysis | kNN Classifier | Image Quality Evaluation | Optical Perception Evaluation Table |
|---------------------------|----------------------------------|----------------------|----------------|-------------------------|------------------------------------|
|                           | Table 2-2                         | Table 2-3            | Table 2-4      | Table 2-5               | Table 2-6                          |
| Local Statistics          | ✓                                 | ✓                    | ✓              | ✓                       | ✓                                  |
| lsmv                      |                                  |                      |                |                         |                                    |
| lsminsc                   | ✓                                 | ✓                    | ✓              |                         |                                    |
| Geometric Filtering       |                                  |                      |                |                         |                                    |
| gf4d                      |                                  | ✓                    |                |                         |                                    |
| Homomorphic Filtering     |                                  |                      |                |                         |                                    |
| homo                      |                                  | ✓                    |                |                         |                                    |
| Diffusion Filtering       |                                  |                      |                |                         |                                    |
| nldif                     |                                  |                      |                | ✓                       |                                    |
| Wavelet Filtering         |                                  |                      |                |                         |                                    |
| wavelet                   |                                  |                      |                |                         | ✓                                  |