Vessel Wall Detection and Blood Noise Reduction in Intravascular Ultrasound Imaging

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Abstract—Scattering from blood limits the contrast between the vessel wall and the lumen in intravascular ultrasound imaging. This makes it difficult to localize the vessel wall, especially on still images. This paper presents a method for automatic detection of vessel walls and reduction of blood noise based on correlation of the RF-signal between adjacent frames. The ultrasound RFsignal is quadrature demodulated, digitized, stored in memory, and transferred to a computer for processing and analysis. The absolute value of the cross-correlation coefficient between two adjacent frames is used to differentiate between stationary and fluctuating signals. Models and numerical calculations presented in this work indicate that the cross-correlation coefficient obtained from a radially dilating vessel wall will be larger than 0.8 under standard 20 MHz imaging conditions. The corresponding value from blood is less than 0.2 for blood velocities exceeding 0.5 $cm s^{-1}$. The blood-noise filter is based on detecting this difference in correlation and displays vessel wall regions with no modifications, while regions detected as blood are rejected. A simplified vessel-wall detector that is suitable for real-time implementation is proposed. The performance of this detector and the blood noise filter are demonstrated by in vitro experiments.

I. INTRODUCTION

SCATTERING from red blood cells (blood noise) varies with the ultrasound frequency and by cell aggregation [1]–[3]. The noise intensity in flowing blood (low cell aggregation) increases dramatically with the ultrasound frequency. This reduces the contrast between the vessel wall and the lumen in intravascular ultrasound imaging, making it difficult to localize the vessel wall and soft plaque. In real-time imaging at 20 and 30 MHz, it is normally possible to see the transition between the blood and the vessel wall due to the temporal fluctuation in the blood noise levels [4]. (It may be more difficult at higher frequencies.) However, on frozen images the blood noise makes it difficult to trace the vessel wall for measurements and three-dimensional (3-D) reconstruction. Scattering from blood also increases with blood cell aggregation, thus the noise intensity changes during the cardiac cycle [3].

A previous paper [5] describes a linear method for blood noise reduction based on lateral (beam-to-beam) low-pass filtering. A Doppler shift from blood is introduced if the ultrasound beam is tilted a few degrees up- or downstream and frequency separation occurs. This filter is effective for blood velocities that exceed a certain limit which ranges between ≈ 10 cm s⁻¹ and ≈ 50 cm s⁻¹ in standard intravascular imaging.

Pasterkamp *et al.* have demonstrated that temporal (frameto-frame) averaging of amplitude data (up to 20 subtraction images) can be used to differentiate between the lumen and static areas [6]. Stationary vessel wall regions are canceled, while fluctuating blood noise turns into a smooth gray pattern. This method offers high spatial resolution, but rapid vessel wall movements will be smeared out.

This paper describes a method for automatic vessel wall detection and blood noise reduction based on two RF-frames [7]. The temporal cross-correlation coefficient (based on ensemble averages) reveals information about the difference in movements that normally exists between vessel wall and blood cells. However, practical differentiation requires estimation by means of temporal and/or spatial averaging. In this paper we consider only spatial averaging to obtain a filter with low temporal smearing at the expense of reduced spatial resolution. Detection is performed by comparing the outcome of the correlation estimate by a threshold. This means that the ability to separate the vessel wall signal from blood noise depends on the estimator's bias and variance, or more precisely, on the corresponding probability density functions (PDF's). Blood noise suppression is simply performed by rejecting areas detected as blood, while areas detected as vessel wall are passed unchanged to the display.

The correlation estimate is related to speckle-tracking algorithms that have been extensively described in the literature [8]–[14]. But instead of tracking the tissue motion from one frame to another by an active search for a best match, our algorithm makes no search (to reduce complexity) but presumes that the vessel wall moves slowly enough for vessel wall signals to be correlated from frame to frame. One estimate is calculated at each point of the image based on two consecutive frames.

Section II of this paper describes the temporal correlation properties and proposes four estimates, two of which are based on complex RF data and two of which are based on amplitude data. In each of these categories, one estimator is computing intensive and one is not. A parametric model for this correlation coefficient is found, and numerical calculations are performed to describe the ultimate performance of the de-

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SYMBOLS	AND	ABBREVIATIONS

$(\mathbf{r}, \boldsymbol{\varphi}, \boldsymbol{\psi})$	Spherical coordinates: r=range, ϕ =lateral beam scan angle.
	ψ =azimuthal beam tilt angle)
R	Radial lag
Φ	Lateral lag
Ψ	Azimuthal lag
а	Transducer radius
c	Velocity of sound
\mathbf{f}_{m}	Frame rate
\mathbf{f}_{α}	Center frequency of transmitted pulse
N_{TX}	Number of cycles in the electrical drive pulse
VB	Blood velocity in the X3-direction
V_{VW}	Vessel wall velocity in the X1/X2-plane
ρ	Cross-correlation coefficient
ρ	Cross-correlation coefficient estimate
ρμο	Estimate based on phase difference
ρΑ	Estimate based on amplitude data
ρ_{AD}	Estimate based on amplitude difference
s(n,r,¢)	Digitized base-band signal (quadrature components)
v(n,r,¢)	Digitized amplitude or video signal
ROI	Region of interest
sv	Sample volume



The ability to visualize soft plaque and coagulated blood is an important clinical task, but it is generally difficult due to low scattering from these types of tissue [1], [15], [16]. However, the fact that scattering from blood is rather strong, and that it fluctuates highly from frame to frame, may actually simplify the detection of soft plaque in that the absence of fluctuating blood noise may indicate soft plaque or coagulated blood.

The symbols and abbreviations that occur most frequently in the paper are listed in Table I.

II. SIGNAL ANALYSIS

A. Correlation Properties

A coordinate system for temporal (frame to frame) analysis of ultrasound catheter data is described in Fig. 1. The center of beam rotation is located in the origin. Blood cells move primarily in the X_3 direction, while vessel wall scatterers move primarily in the X_1/X_2 plane. Both vessel wall dilation and catheter tip movements (catheter "whip") appear as a vessel wall movement relative to the catheter.

The RF signal received is demodulated to its baseband inphase and quadrature components. This complex analog signal $u(t, r, \phi)$ is acquired along a spiral in the space/time coordinate system as illustrated in Fig. 2(a), and it is specified by one temporal and two spatial variables (which are related). The signal is further digitized and treated as discrete plane images $s(n, r, \phi)$ as illustrated in Fig. 2(b). The discrete variable ndenotes the frame number, and it is related to the temporal



Fig. 1. Coordinate system for intravascular ultrasound imaging. The location of the image point is set constant to (r, ϕ) when the signal is observed along the temporal coordinate (frame to frame). Blood scatterers traverse through the sample volume with an azimuthal velocity $V_{\psi B}$ component, while vessel wall scatterers traverse primarily with a radial V_{rVW} and/or lateral $V_{\phi VW}$ velocity component.



Fig. 2. (a) Data are physically acquired in a spiral plane along the temporal axis. (b) The digitized signal is treated as plane images, addressed by the three discrete variables: (n, r, ϕ) .

variable t and the frame rate f_m by

$$n = \text{integer}\,(t \cdot f_m). \tag{1}$$

The measured signal from one specific point (r, ϕ) of the image will be a discrete temporal sequence of samples, either acquired from a blood region, a vessel wall, or from a transition region. The temporal sampling frequency equals the frame rate, and the interval τ between two frames is the inverse of the frame rate

$$t = 1/f_m.$$
 (2)

The signal from a region of a vessel wall will be highly correlated from frame to frame if the vessel wall movement is small relative to the size of the point spread function. This can be achieved by proper selection of the frame rate in relation to the size of the sample volume and the velocity of the wall. Typical vessel-wall velocities range below a few millimeters per second which corresponds to frame rates in the range of 10–40 frames per second (f.p.s.). Blood cells normally move much faster (typically 10–100 times [5]) than the vessel wall cells which means that blood noise will normally be uncorrelated with the same setting. The temporal cross-correlation coefficient yields information about these correlation properties at any point (r, ϕ) of the image

$$\rho(\tau; r, \phi) = \frac{\langle s(n, r, \phi) \cdot s^*(n+1, r, \phi) \rangle}{\sqrt{\langle |s(n, r, \phi)|^2 \rangle \cdot \langle |s(n+1, r, \phi)|^2 \rangle}}.$$
 (3)



Fig. 3. The absolute value of the temporal cross-correlation coefficient at a fixed point (r, ϕ) versus interval τ between observations (frames). Differences in velocities allow vessel-wall and blood noise regions to be differentiated by proper selection of τ .



Fig. 4. The cross-correlation coefficient estimates process two overlapping (no spatial lag) ROI's from adjacent frames. The size of the ROI's is X samples in the radial direction and Y samples in the lateral direction.

The parameter τ is the temporal lag that specifies the interval between the two observations (frames). The symbols $\langle \cdot \rangle$ and * denote ensemble averaging and complex conjugation, respectively. Vessel-wall regions are characterized by $|\rho(\tau; r, \phi)| \approx 1$, while blood regions are characterized by $|\rho(\tau; r, \phi)| \approx 0$ as illustrated schematically in Fig. 3.

B. Cross-Correlation Coefficient Estimates

Four different estimates of the cross-correlation coefficient are proposed in this section. Two are based on the linear RF signal in quadrature component form $s(n, r, \phi)$, while the other two are based on a compressed amplitude (video) signal defined by

$$v(n,r,\phi) = f(|s(n,r,\phi)|) \tag{4}$$

where the compression function $f(\cdot)$ is a numerical approximation to an analog log-amp with dynamic range ≈ 60 dB. All estimates include spatial averaging over a region of interest (ROI) of size $X \cdot Y$, and the input data are taken from two adjacent frames as illustrated in Fig. 4. The four estimates are listed below:

i) The first estimate ρ is the absolute value of a direct implementation of (3), where ensemble averaging is replaced by spatial averaging. This estimate is based on the quadrature components of the signal, and normalization is performed after averaging

$$\hat{\rho}(\tau; n, r, \phi) = \left| \frac{\sum_{\text{ROI}} s(n, r, \phi) \cdot s^*(n+1, r, \phi)}{\sqrt{\sum_{\text{ROI}} |s(n, r, \phi)|^2 \sum_{\text{ROI}} |s(n+1, r, \phi)|^2}} \right|.$$
(5)

ii) The second estimate is a simplified version of $\hat{\rho}$, where normalization is performed before averaging. Spatial averaging is performed on a frame of phase difference unit vectors (PDUV) between the two input frames

$$\hat{\rho}_{PD}(\tau; n, r, \phi) = \left| \frac{1}{XY} \sum_{\text{ROI}} z_{\text{PDUV}}(\tau; n, r, \phi) \right| \quad (6a)$$

where

$$z_{\text{PDUV}}(\tau; n, r, \phi) = \frac{s(n, r, \phi) \cdot s^*(n+1, r, \phi)}{|s(n, r, \phi) \cdot s^*(n+1, r, \phi)|}.$$
 (6b)

iii) The third estimate is a direct implementation of (3) with compressed amplitude (A) signals. Once again, normalization follows averaging, as in (7a) shown at the bottom of the page, where the local mean value estimate is given by

$$v_m(n,r,\phi) = \frac{1}{XY} \sum_{\text{ROI}} v(n,r,\phi).$$
(7b)

iv) The fourth estimate is a simplified version of $\hat{\rho}_A$, in which normalization is performed prior to averaging. This method is particularly simple in that spatial averaging is performed on a (normalized) amplitude difference (AD) image

$$\hat{\rho}_{\rm AD}(\tau; n, r, \phi) = \frac{1}{XY} \sum_{\rm ROI} z_{\rm AD}(\tau; n, r, \phi)$$
(8a)

$$z_{\rm AD}(\tau; n, r, \phi) = \frac{K}{K + |v(n, r, \phi) - v(n+1, r, \phi)|}.$$
 (8b)

The number of numerical operations required to calculate these estimates directly from the equations is rather high: it ranges between 5XY and 10XY for one point (r, ϕ) of the image. The implementation can be simplified by changing the order in which calculations are performed, i.e., by realizing the algorithms as a cascade of frame-based operations; the estimator $\hat{\rho}_{AD}$, for example, can be realized by calculating the

$$\hat{\rho}A(\tau;n,r,\phi) = \frac{\sum_{\text{ROI}} [v(n,r,\phi) - v_m(n,r,\phi)] \cdot [v(n+1,r,\phi) - v_m(n+1,r,\phi)]}{\sqrt{\sum_{\text{ROI}} [v(n,r,\phi) - v_m(n,r,\phi)]^2 \sum_{\text{ROI}} [v(n+1,r,\phi) - v_m(n+1,r,\phi)]^2}}$$
(7a)

modified amplitude difference for all points in the image (8b). Spatial averaging can be realized by a radial moving averaging operation followed by a lateral counterpart (consisting of simple sums and differences). This estimate is a variant of the well-known sum-absolute-difference algorithm (SAD) [8], [10].

This frame-based approach simplifies the implementation of $\hat{\rho}_{AD}$ and $\hat{\rho}_{PD}$ dramatically. The required number of operations per pixel is now 8–10, and it is independent of the size of the ROI.

C. Parametric Signal and Correlation Model

A parametric model for the temporal cross-correlation coefficient (3) is described in this section. This model is used in numerical calculations in Section III to quantify estimator performance limits.

The model is based on the following assumptions: i) The point spread function $h(R, \Phi, \Psi)$ is spatially invariant and separable in the radial and angular directions, and ii) the scatterers are randomly distributed and small compared to the wavelength.

This means that the received RF-signal can be written as a convolution between the point spread function and the spatial scattering distribution [17]–[19]

$$R_S(R,\Phi,\Psi) = h(-R,-\Phi,-\Psi) \otimes h(R,\Phi,\Psi).$$
(9)

A parametric expression for R_S is found by modeling the acoustic pulse by a sinusoidal excitation voltage consisting of N_{TX} cycles at frequency f_o , weighted by a cosine-shaped envelope. The beam profile is described by the far-field beam intensity from a plane circular piston transducer excited uniformly by continuous waves. Circular beam symmetry equalizes the lateral and azimuthal terms of the point spread function. We hence use the following baseband model for the point spread function:

$$h_{\text{mod}}(R, \Phi, \Psi) = \cos\left(\frac{2\pi f_o}{cN_{TX}}R\right) \left(\frac{2J_1(\pi z_1)}{\pi z_1}\right)^2 \cdot \left(\frac{2J_1(\pi z_2)}{\pi z_2}\right)^2$$
(10a)

where $|R| \leq c N_{TX}/4f_o$ and

$$z_1 = \frac{2afo}{c}\sin(\Phi)$$
 and $z_2 = \frac{2af_o}{c}\sin(\Psi)$ (10b)

and J_1 is the Bessel function of the first kind and first order. A parametric model for the autocorrelation function is now found by inserting (10a) and (10b) into (9)

$$R_{S \bmod}(R, \Phi, \Psi) = h_{\text{mod}}(R, \Phi, \Psi) \otimes h_{\text{mod}}(R, \Phi, \Psi).$$
(11)

A parametric model for the temporal cross-correlation coefficient in (3) is now found by assuming uniform velocity fields and inserting the following expressions $R = V_r \tau$, $\Phi \approx V_{\phi} \tau / r_o$ and $\Psi \approx V_{\psi} \tau / r_o$ for scatterer movement into (11):

$$\rho_{\rm mod}(\tau, V_r, V_{\phi}, V_{\psi}) = R_{S\,\rm mod}(V_r \tau, V_{\phi} \tau/r_o, V_{\psi} \tau/r_o). \tag{12}$$

Spatial velocity gradients as well as diffusion will cause the correlation lengths to be shorter than stated by the model. The



Fig. 5. Simulated vessel-wall correlation versus interval between adjacent frames τ , and radial vessel-wall velocity V_{rVW} , based on the parametric model for a 20 MHz 8F catheter. Solid lines: $SV_r = 0.5 SV_{\phi}$. Dashed lines: limited radial bandwidth, $SV_r = SV_{\phi}$.

lateral width of the sample volume SV_{ϕ} is, in the following, defined as the width of the main lobe (between the first zeros) according to the parametric model.

D. Estimator Performance Limits

This section presents some numerical calculations that were performed to demonstrate the optimal performance limits for automatic vessel wall and blood noise differentiation. The temporal correlation curves in Fig. 3 that represent ensemble averaging are quantified by plotting the parametric model $\rho_{\rm mod}(\tau)$ for some typical vessel-wall and blood velocities. The plots include radial movement of vessel wall scatterers and azimuthal movement of blood cells (the latter plot also applies for vessel-wall scatterers that move perpendicular to the scan plane). Lateral vessel-wall movement is not included, since the lateral correlation length normally is longer than the radial correlation length. Tissue deformation such as rotation and compression will decrease the correlation, but these effects are not described.

The shapes of the curves are all the same and are given by (12). What differs is the horizontal scaling which is determined by the actual scatterer velocity. The following parameters were used for the calculations: a = 0.7 mm, $f_o = 20 \text{ MHz}$, $N_{TX} = 3$ [full bandwidth (BW)], $N_{TX} = 9$ (limited BW), and $c = 1560 \text{ m s}^{-1}$.

The result for a radially dilating vessel wall is shown in Fig. 5. Two different situations are given, both at depths of $r_o = 3 \text{ mm}$: i) full radial bandwidth, where the radial length of the sample volume is approximately 50% of the lateral width $(SV_r = 0.5SV_{\phi})$, and ii) reduced radial bandwidth, where $SV_r = SV_{\phi}$. Radial vessel wall velocities in intravascular imaging are estimated to exceed 2.5 mm s⁻¹ only rarely [5]. The figure shows that $\rho_{\text{mod}} > 0.8$ for velocities below this value, given a frame rate of 30 f.p.s. and limited bandwidth. The calculation indicates that one can achieve high correlation from the vessel wall by keeping the frame rate high, and if necessary, limiting the radial bandwidth.

The correlation properties for uniform and laminar blood flow (at a depth $r_o = 3$ mm) are shown in Fig. 6. The



Fig. 6. Simulated blood noise correlation versus interval between adjacent frames τ and blood velocity $V_{\psi B}$, based on the parametric model for a 20 MHz (8F) catheter. The sample volume is located at a depth $r_o = 3$ mm.

correlation is low ($\rho_{\rm mod} < 0.3$) for velocities exceeding 0.4 cm s⁻¹ at 30 f.p.s. This means that blood noise will be uncorrelated during most of the cardiac cycle in human arteries. The curve in Fig. 6 represents an upper limit for the correlation time. Turbulence and scatterer diffusion will further reduce the correlation for blood signal in an *in vivo* situation.

The ability to differentiate between the pulsating vessel wall and the blood noise on the basis of two consecutive frames is promising. Differentiation is performed by comparing the outcome of the correlation estimator with a threshold T_r and assigning values exceeding the threshold to a vessel-wall region and values below the threshold to a blood region. The quality of this process depends on the variance of the estimates as well as additional noise and other reasons for decorrelation.

III. EXPERIMENTS AND RESULTS

A. Instrumentation

Experimental data were acquired with an intravascular scanner¹ and modified to collect sequences of full-image RF-data. Up to 14 frames were stored in memory and transferred to the computer for further analysis. The frame rate was limited by the bus capacity to $f_m = 6.6$ f.p.s. in this mode which is far too low for *in vivo* studies (the vessel wall signal would decorrelate). This limitation can be eliminated if the algorithm is implemented in a modern scanner. The in-phase and quadrature components were digitized by two 8-bit AD-converters at a 20 MHz sampling rate. The image format is $N_r = 256$ samples per beam and $N_b = 256$ beams per revolution.

A modified 20 MHz (8F) catheter with a rotating mirror was used in all experiments. The catheter was shortened to 30 cm and inserted into a stiff metal tube to reduce electromagnetic interference, ensure stable mirror rotation, and increase the catheter's lifetime. A 280-degree acoustic window was cut in the tube, and the distal heat-shrink tubing was removed to reduce catheter reverberations. The ultrasound beam was tilted approximately eight degrees toward the proximal end of the catheter. The electrical drive pulse was four cycles in all experiments, but the acoustic pulse duration was longer due to limited bandwidth of the transducer (≈ 9 cycles).

A tissue-mimicking phantom was made for two purposes: i) to mimic a region of small stationary randomly distributed scatterers for signal model verification, and ii) to mimic a moving blood vessel to demonstrate detector performance.

The phantom was made by mixing 0.5% by weight Sephadex particles² in an agar gel³ and allowing it to cure around a plastic bolt shaped as illustrated by the white area in Fig. 9(a). The bolt was removed after solidification, leaving a regular structure in the lower half of the phantom. The upper half was shaped like a typical blood vessel where the structure at the left mimics an intimal flap resulting from balloon angioplasty. All experiments were performed in water tanks.

Blood was mimicked by mixing 0.2% by weight Sephadex particles in water. This liquid is convenient to work with, but differs from blood in viscosity and scattering properties. We considered this not to be critical, since the main purpose of the experiments is to illustrate the statistical properties of correlated vessel wall signal and uncorrelated blood noise in two separate areas. Making the viscosity more equal to that of blood would make it more difficult to obtain uncorrelated signals from the blood mimicking liquid.

The Sephadex particles are three to four times larger than blood cells. This will affect the scattering strength and the frequency dependency (at least in a broad-band system). However, the impact on our (narrow-band) experiments is expected to be low, since all experiments are performed with uncorrelated blood noise signals.

The average number of particles in the sample volume was estimated to be at least $N_{sv} = 98$. This number is lower than in blood but high enough to assume that the scattered signal from this liquid can be modeled as a Gaussian process. When a process is Gaussian, the statistical properties of the estimated cross-correlation coefficient are solely given by the point-spread function and frame rate of the system.

The following parameters were used to estimate N_{sv} : sample volume radial length = 0.2 mm (\approx 5 cycles), sample volume cross-sectional area = 1.54 mm² (equal to the transducer area), the particles fills 74% of the powder-volume, and the density of the powder is measured to be 0.79 g mL⁻¹.

B. Model Verification

An experiment was carried out to verify the parametric model for the autocorrelation function $R_{Smod}(R, \Phi, \Psi)$ given in (11) (radial and lateral properties only). The test was performed by acquiring one data frame from a homogenous region of the phantom. The normalized autocorrelation function was calculated from two different estimates (autocorrelation counterparts to ρ and $\hat{\rho}_{PD}$), and the ROI was selected largely

²Sephadex G-25/Superfine, Pharmacia Fine Chemicals, Uppsala, Sweden.

³KEBO Lab, S-163 94, Spånga, Sweden.

¹CVIS Insight, Cardiovascular Imaging Systems, Inc., CA.



Fig. 7. (a) Mesh plot of modeled normalized autocorrelation function: $R_{S \mod}(R, \Phi, 0)$. (b) Mesh plot of experimentally measured normalized autocorrelation function $R_{\exp}(R, \Phi)$ (based on the ρ -estimator). (c) Radial plots through the peak of $R_{S \mod}, R_{S \exp}$, and $R_{P \operatorname{Dexp}}$. (d) As in (c), but lateral plots.

to come close to the expected value of the estimators

$$R_{\exp}(R,\Phi) = \left| \frac{\sum_{\text{ROI}} s(r,\phi) \cdot s^*(r+R,\phi+\Phi)}{\sqrt{\sum_{\text{ROI}} |s(r,\phi)|^2 \sum_{\text{ROI}} |s(r+R,\phi+\Phi)|^2}} \right|$$
(13)

$$R_{\rm PDexp}(R,\Phi) = \left| \frac{1}{XY} \sum_{\rm ROI} w_{\rm PDUV}(R,\Phi) \right|$$
(14a)

where

$$w_{\text{PDUV}}(R,\Phi) = \frac{s(r,\phi) \cdot s^*(r+R,\phi+\Phi)}{|s(r,\phi) \cdot s^*(r+R,\phi+\Phi)|}.$$
 (14b)

The ROI used in the estimation was 100 times larger (in area) than the size of the sample volume. The following parameters were inserted into (11): $a = 0.7 \text{ mm}, f_o = 20 \text{ MHz}, N_{TX} = 9$, and $c = 1560 \text{ m s}^{-1}$.

The results are shown in Fig. 7, where (a) is a mesh plot of the model $R_{S \mod}(R, \Phi, 0)$, while (b) is a mesh plot of the experimental function $R_{\exp}(R, \Phi)$. A qualitative comparison is made in (c) and (d), where radial and lateral plots through the peak are shown, respectively (solid = model, dashed = experimental). The third curve is R_{PDexp} , the experimental counterpart to $\hat{\rho}_{\text{PD}}$. There is a close fit between the proposed model $R_{S \mod}$ and the experimental result R_{\exp} . The plots also indicate that the estimator R_{PDexp} has a relatively low bias when the ROI is large.

C. Estimator Statistics Separability

This section illustrates the ability of the method to discriminate between vessel-wall signals and blood noise by estimating the corresponding PDF's. Measured histograms were calculated from experimental data to approximate the PDF's.

The cross-correlation coefficient estimate outputs numbers between zero and one (due to the normalization). It is a stochastic variable whose statistics depend on the location of the sample volume and the properties of the scattering medium. When the sample volume is located in regions of 100% stationary scatterers (and no noise), the outcome of the estimator will equal one, and the probability density function will be a Dirac pulse. As a small scatterer movement is introduced, outcomes less than unity will occur, and the probability density function will be narrow (low variance) with mean value less than, but close to, one. Further increasing the velocity causes the mean value of the stochastic variable to drop in correspondence to the shape of the normalized spatial autocorrelation function (see Fig. 7), and the variance increases [20]. It has been shown that the stochastic variable has an approximately Gaussian distribution for partially correlated signals, and the distribution changes toward a Rayleigh distribution as the scatterer velocity is further increased [21].

The histograms for blood regions were obtained by acquiring two frames of data from water that contained 0.2% by weight Sephadex particles; uncorrelated data were obtained by mixing the water during acquisition. The estimator $\hat{\rho}_{PD}$ was calculated for all points of the image (for three different ROI sizes: $1 \times 1, 2 \times 2$, and 3×3 times the size of the sample volume), and the histograms were calculated from a region that was approximately 450 times larger (in area) than the sample volume (in contrast to using a large number of independent realizations, which is a time-consuming operation).

The results are shown in Fig. 8 (left histograms) in which a Rayleigh distribution is plotted for comparison (parametric curve fitting based on measured data).

The histograms for vessel wall regions were obtained by acquiring one single frame of data from the tissue-mimicking phantom. A radial tissue movement was mimicked by making a copy of this frame and applying a radial shift to all beams. (It is difficult to make a phantom that expands radially without rotation or compression effects.) The estimator $\hat{\rho}_{PD}$ was then calculated, and a number of realizations with partially overlapping ROI's was used to build the histogram (partial overlap was accepted to reduce the extent of the experiment). The result is shown in Fig. 8 (right histogram) in which a parametric Gaussian curve fitting has also been shown for comparison.

Fig. 8 illustrates that the estimator variance decreases as ROI size increases, making it simpler to separate the two. Almost perfect separation is possible in (b) and (c). These experiments provide a statistical description of $\hat{\rho}_{\rm PD}$ for uncorrelated blood noise and for one particular vessel-wall velocity. A complete statistical description requires a large number of experiments with different vessel-wall velocities. However, this example demonstrates that automatic differentiation is possible by proper selection of the ROI size.

A simple detector has been selected in this work: $\hat{\rho}_{\rm PD}$ is compared with a threshold T_r . Values exceeding T_r are assigned to a vessel-wall region, while values below are assigned to a blood region. Knowing the statistics (varies with



Fig. 8. Measured histograms of the cross-correlation coefficient estimator $\rho_{\rm PD}$ from a blood-mimicking liquid (left) and a vessel-wall phantom (right). The estimator is approximately Rayleigh-distributed for uncorrelated (blood) signals and approximately Gaussian-distributed for partially correlated (vessel wall) signals. Variance decreases and separability increases with increasing ROI size.

the application), one can calculate the probability of correct vessel-wall detection and the probability of detecting blood noise as a vessel wall (false alarm) [22]. The threshold should be manually adjusted and set as high as possible to minimize blood noise but low enough to ensure almost perfect detection of the vessel wall.

D. Phantom Image Example

The performance of the detector is demonstrated by an *in vitro* experiment. The phantom was imaged by a catheter, and the phantom was translated horizontally in a water tank during data acquisition, generating a radial tissue movement in the 3 and 9 o'clock directions, a pure lateral movement at 12 and 6 o'clock, and rotation (result of combined radial and lateral movement) in the other regions. An image of the phantom is shown in Fig. 9(b). A contour was manually drawn (b) and copied to the other images to make comparison easier. This contour does not fit exactly the shape of the phantom (geometric distortion caused by catheter beam tilting). A black sector is drawn from 11 to 3 o'clock to hide the distracting echoes from the metal tube.

Sephadex particles were immersed in water, and this liquid was mixed to ensure particle velocities of several cm s⁻¹ which means that the signals will be uncorrelated from frame to frame ($V_{\phi B} > 2.5 \text{ mm s}^{-1}$ is sufficient according to Fig. 6). The tissue phantom velocity was set to $V_{vw} = 0.5 \text{ mm s}^{-1}$ while the frame rate was set to $f_m = 6.6 \text{ f.p.s.}$ The reason for selecting such a low phantom velocity is to achieve high The result of including blood mimicking particles is shown in Fig. 9(c); the contrast between the phantom and the lumen is substantially reduced. A sequence of 14 frames was acquired, and the estimate $\hat{\rho}_{PD}$ was applied for three different ROI sizes followed by the threshold detector. The resulting detector bitmaps are shown in Fig. 9(d)–(f). The rectangles indicate the size of the ROI at each particular depth. These bitmaps are multiplied by the original image (b) to form the final blood-noise rejected images which are shown in Fig. 9(g)–(i). The result obtained from Fig. 8 is verified here; the ability to detect and reject blood noise increases by the degree of spatial averaging at the expense of reduced spatial resolution.

The entire sequence was played as an endless loop (cineloop) on the computer to demonstrate the dynamic performance of the algorithm. The vessel-wall detector is accurate and stable when the ultrasound beam hits a smooth surface relatively perpendicularly, leaving a stable representation of the moving phantom structure on the screen. However, the output of the detector is more subject to variations from frame to frame when the geometry becomes more complex, especially when a phantom edge is approximately parallel to the beam axis, and when the ROI contains blood noise and vessel-wall signals simultaneously. The phantom representation is subject to flickering. Ways of reducing this flickering effect include keeping the ROI size low and applying a smoother reject function (which allows more than the two options in the detection operation).

E. Amplitude-Based Estimates

A comparison was made between ρ , $\hat{\rho}_{PD}$, ρ_A , and $\hat{\rho}_{AD}$ by applying the same method as in Fig. 8 to all estimates. The purpose of this procedure was to illustrate that the statistical properties of the amplitude-based estimates differ significantly from those of the RF-based; see Fig. 10. Our parametric model ρ_{mod} cannot be applied to ρ_A and $\hat{\rho}_{AD}$. However, the plots indicate that vessel wall and blood signals still can be differentiated. A comparison between RF-based and amplitude-based estimators is therefore suggested for future work since amplitude based estimators are simpler in that the video-signal can be used.

IV. SUMMARY AND DISCUSSION

This paper describes a method for automatic vessel wall detection and blood noise rejection. The algorithm differentiates between the vessel wall and blood and applies a hard reject function in regions detected as blood. It is based on a normalized cross-correlation coefficient estimated from two consecutive frames, where the estimator variance is reduced by spatial averaging. Differentiation is achieved when the vessel wall signal is correlated from frame to frame, while blood noise is not, given a certain frame rate and other instrument related parameters. Short detection time (two frames only) minimizes temporal blurring during real-time imaging of pulsating vessel walls. This allows rapid 3-D acquisition (ECG-triggered pull-back) as well.



Fig. 9. (a) Geometric shape of the vessel-wall mimicking phantom. (b) Ultrasound image (20 MHz) of horizontally translating phantom, water in lumen. The contour drawn in this image is copied to the other images. (c) Same as (b), but with Sephadex particles in the water. (d)–(f) Vessel wall detector (thresholded estimator $\hat{\rho}_{\rm PD}$) versus ROI size. (g)–(i) Final result versus ROI size. The image in (c) is multiplied by (d) to (f), respectively. Luminar noise is reduced substantially with increasing ROI size at the expense of reduced spatial resolution.

A theoretical model is provided that quantifies actual vessel wall and blood velocities that make separation possible, given some typical imaging parameters and otherwise idealized conditions. Numerical calculations and experiments illustrate that separation is possible at 20 MHz ($f_m = 15$ f.p.s.) when the radial vessel wall velocity is less than ≈ 0.5 mm s⁻¹ and the blood velocity exceeds ≈ 0.5 cm s⁻¹. This indicates that the filter will be effective during most of the cardiac cycle.

The performance of the algorithm will be affected by several factors in a clinical setting: acoustic and electronic noise, catheter and vessel wall movements, a variable blood flow, and the fact that the sample volume overlaps both blood and tissue at the lumen edge. It is not the intention of this paper to characterize and describe these factors, partly due to limitations in the scanner which inhibits *in vivo* RF-experiments. The experiments have been carried out at 20 MHz only and designed so that the statistical properties of various

estimates can be illustrated under approximately idealized conditions.

In a setting with little acoustic and electronic noise, the following can be said about the performance of the algorithm: The ability to differentiate between a vessel wall region and a blood region will be independent of the signal levels, since the cross-correlation coefficient normalizes the signals. This means that cyclic changes in the scattering from blood through the cardiac cycle (due to blood cell aggregation) will not affect the performance. Increasing the ultrasound frequency will affect the scattering intensity from blood, but this will, for the same reason, not affect the performance. However, an increased ultrasound frequency will, if the spatial resolution increases, cause the autocorrelation function to be narrower, thus reducing the correlation lengths. The result is an algorithm that is less robust against vessel wall movements and more robust against blood velocities. However, this can be compensated for by increasing the frame rate.



Fig. 10. Measured histograms of ρ , $\hat{\rho}_{PD}$, ρ_A , and $\hat{\rho}_{AD}$ from a blood-mimicking liquid (left) and a vessel-wall phantom (right). Separation is possible for all estimates although the statistical properties differ.

The performance of the algorithm in a noisy environment depends primarily on the correlation properties and intensity of the noise sources versus the properties and intensity of the vessel wall signals and the blood noise. Uncorrelated electronic noise will, in the presence of correlated vessel wall signal, reduce the probability of detecting the vessel wall correctly. Correspondingly, correlated acoustic noise, like stationary catheter or tissue reverberations, in the presence of uncorrelated blood noise, will reduce the probability of detecting blood areas correctly. The performance will therefore, in the presence of stationary clutter noise, improve when the scattering strength from blood rises due to blood cell aggregation or an increased ultrasound frequency.

In a recent publication we demonstrated that the amplitudebased estimator ρ_A performs well when applied to *in vivo* data from a pig ascending aorta [23]. The main noise source in these images is stationary reverberations from the catheter that dominates the blood noise. As one would expect, this noise is detected as stationary and passed through with no rejection.

The function ρ is a computing intensive estimate of (3) using spatial averaging. The simpler estimate $\hat{\rho}_{PD}$ is shown by experiments to perform almost as well as ρ , and both estimates are closely described by the parametric model. The amplitude-based estimates ρ_A and $\hat{\rho}_{AD}$ also allow separation between vessel wall and blood, but a qualitative comparison is not provided in this work. The simplicity of $\hat{\rho}_{AD}$, and the fact that a majority of ultrasound scanners still do not provide digital RF-data, makes this estimate particularly attractive.

The estimate $\hat{\rho}_{PD}$ is suggested for real-time implementation due to its simple form and high performance. There are reasons to believe that the implementation can be further simplified by reducing the number of bits in the PDUV representation to two to three for the real and imaginary parts. Initial testing performed at our laboratory confirms this. This is motivated by the fact that the correlation estimate does not change dramatically when one or both of the input signals are passed through a hard limiter (Bussgang's relation) [24], [25]. Equation (6b) can be implemented in a lookup table at the same rate as the AD-conversion. The remainder are complex summations, one division (scaling) and one magnitude operation (6a), which can be performed in a field programmable gate array (FPGA) also at the same rate.

The most critical part of the algorithm is that of maintaining high vessel-wall correlation. Several factors cause decorrelation: a) scatterer movement within the scan plane; b) scatterer movement out of the scan plane, i.e., in the azimuthal direction (along the catheter axis) (note that the radial movements will yield an azimuthal component in case of beam tilting); c) tissue compression and rotation; d) electronic noise; and e) nonuniform mirror or transducer rotation (from frame to frame). Except for a), none of these effects are quantified in this paper. However, adequate vessel wall correlation can be achieved by:

1) Keeping the frame rate high to minimize movement from frame to frame. Drawbacks are reduced lifetime of the mechanical drive wire in the catheter (if any), high data throughput capacity requirements, and a rise in the velocity limit at which blood noise can be differentiated.

- 2) Increasing the correlation length in the radial direction by applying a digital bandwidth limiting filter in the radial direction prior to vessel wall detection. Drawbacks include reduced radial resolution of the detector.
- 3) Tracking vessel-wall motion within the scan plane by searching for the maximum peak in the cross-correlation coefficient by including spatial lags (not only temporal lag). This method increases the computation requirements substantially (by a factor equal to the number of search positions).

Our algorithm is based on two consecutive RF-frames, where spatial averaging is applied to reduce estimator variance. The algorithm described by Pasterkamp *et al.* is based on two consecutive amplitude frames, and temporal averaging is applied to improve the quality of the detector. The best result would probably be obtained by including several consecutive RF-frames in the estimator and allow the user to adjust the degree of spatial and/or temporal averaging depending on the actual application.

The authors believe that there is great potential in the proposed method if one can ensure a high degree of correlation in the vessel-wall signal. This can most simply be achieved by keeping the frame rate high. There is room for increasing the frame rate dramatically, since limited penetration allows frame rates in the order of several hundred frames per second (in the 10–50 MHz frequency range). The price paid is a higher blood velocity limit at which the filter is effective. However, this may still be within an interesting range (a few centimeters per second). The algorithm reduces fluctuating blood noise thus improving the detection of soft plaque and coagulated blood.

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