ULTRASONIC TECHNIQUE FOR IMAGING TISSUE VIBRATIONS: PRELIMINARY RESULTS

Siddharta Sikdar,* Kirk W. Beach,† Shahram Vaezy,‡ and Yongmin Kim*

*Image Computing Systems Laboratory, Departments of Electrical Engineering and Bioengineering; †Department of Surgery; and ‡Center for Industrial and Medical Ultrasound, University of Washington, Seattle, WA, USA

(Received 9 January 2004, revised 9 October 2004, accepted 14 October 2004)

Abstract—We propose an ultrasound (US)-based technique for imaging vibrations in the blood vessel walls and surrounding tissue caused by eddies produced during flow through narrowed or punctured arteries. Our approach is to utilize the clutter signal, normally suppressed in conventional color flow imaging, to detect and characterize local tissue vibrations. We demonstrate the feasibility of visualizing the origin and extent of vibrations relative to the underlying anatomy and blood flow in real-time and their quantitative assessment, including measurements of the amplitude, frequency and spatial distribution. We present two signal-processing algorithms, one based on phase decomposition and the other based on spectral estimation using eigen decomposition for isolating vibrations from clutter, blood flow and noise using an ensemble of US echoes. In simulation studies, the computationally efficient phase-decomposition method achieved 96% sensitivity and 98% specificity for vibration detection and was robust to broadband vibrations. Somewhat higher sensitivity (98%) and specificity (99%) could be achieved using the more computationally intensive eigen decomposition-based algorithm. Vibration amplitudes as low as $10^{-4}$ m were measured accurately in phantom experiments. Real-time tissue vibration imaging at typical color-flow frame rates was implemented on a software-programmable US system. Vibrations were studied in vivo in a stenosed femoral bypass vein graft in a human subject and in a punctured femoral artery and incised spleen in an animal model. (E-mail: ykim@u.washington.edu) © 2005 World Federation for Ultrasound in Medicine & Biology.

Key Words: Bruits, Ultrasound, Real-time tissue vibration imaging, Vibration detection and estimation, Parametric modeling, Phase decomposition, Eigen decomposition, Programmable ultrasound system, Assessment of arterial stenoses, Localizing internal bleeding.

INTRODUCTION

It has now been established that vascular sounds associated with stenoses, aneurysms, arteriovenous fistulae and pseudoaneurysms are produced by the forces exerted on vessel walls by eddies produced when blood flows from a high-pressure region to a low-pressure region through a narrow orifice (Foreman and Hutchinson 1970; Kirkeeide et al. 1977). The pressure fluctuations in the eddies cause local vibrations in the vessel wall and surrounding tissue and manifest either as audible "bruits" and "murmurs" or palpable "thrills" when they reach the skin surface. The power spectrum of the vibration exhibits a frequency peak called the "break frequency" that is directly related to the diameter of the orifice and the local flow velocity through the Strouhal number.

Auscultation (passive listening using a stethoscope) is routinely used to qualitatively assess the loudness and pitch of bruits and murmurs in many vascular diseases, such as renovascular hypertension, coronary artery disease, peripheral artery disease and internal bleeding (Albers 1994; McDonald et al. 1975; McGee and Boyko 1998; Semmlow et al. 1983). Phonoangiography and phonocardiography were developed to quantify the spectral content of bruits and murmurs recorded with a sensitive microphone (Lees and Dewey 1972) and carotid phonoangiography was successfully used to estimate the degree of carotid artery stenosis in multiple clinical trials (Duncan et al. 1975; Knox et al. 1981). However, auscultation and phonoangiography lack sensitivity and specificity because they are limited to diagnosing high-intensity vibrations that reach the skin surface, and the origin of the vibrations cannot be clearly resolved. Cur-
rently, there is no diagnostic tool to quantitatively image the vibrations associated with bruits at their origin. Therefore, although tissue vibrations have been shown to be important in diagnosis, their clinical use is currently limited.

Advances in duplex and color-flow ultrasound (US) in the last 2 decades have had a significant clinical impact on vascular diagnosis, with the simultaneous availability of anatomy and flow images in real time. Recently, ultrasonic tissue Doppler imaging (TDI) was introduced for assessment of abnormal wall motion in the cardiac wall as well as in arteries (Bonnefous et al. 2000). This concept could be further extended to use US for the transcutaneous assessment of vibrations at their origin deep in tissue. In conventional color-flow US images, tissue vibrations from abnormal blood flow produce characteristic speckled artefacts in the surrounding tissue (Middleton et al. 1989). These artefacts indicate tissue vibrations and are useful for recognizing stenoses (Strandness 1993). However, they are difficult to interpret and are not quantitative. Tissue vibrations have been previously studied using 1-D pulsed Doppler US. Vibrations in the cardiac and arterial walls were studied using a phase-tracking method (Kanai et al. 1996). Plett (2000) proposed a wavelet-based method for detecting and characterizing arterial vibrations. These pulsed Doppler-based techniques have a limited field-of-view along a single scan line. Furthermore, their processing was done off-line, so it was not possible to create images interactively in real-time. Researchers in ultrasonic elasticity imaging have also been interested in imaging externally induced vibrations, which are typically narrowband with known frequencies (Yamakoshi et al. 1990).

We propose a new tissue vibration imaging mode for US instruments in which vibrations produced by blood flow eddies are detected and color-coded according to their amplitude and frequency and overlaid on the B-mode and/or color-flow image in real time. The tissue vibration imaging mode can be used for locating the origin of vibration more precisely relative to the anatomy and/or for obtaining simultaneous information about vibrations and the underlying blood flow. Our proposed vibration imaging algorithms use quadrature-demodulated data acquired during conventional ultrasonic color-flow imaging and utilize the clutter signal, normally suppressed in conventional color-flow imaging, to detect and characterize tissue vibrations. We have developed two vibration imaging algorithms based on parametric modeling of vibrations and the criteria to distinguish between clutter, blood flow and vibrations. These algorithms are evaluated for their efficacy in detecting vibrations through simulation. Experimental results are presented for the estimation accuracy of vibration amplitude and frequency. The potential clinical utility of tissue vibration imaging to localize internal bleeding sites and assess arterial stenoses is discussed based on preliminary results from in vivo studies.

**METHODS AND MATERIALS**

**Signal model**

The tissue being imaged can be approximated with \( S \) point scatterers randomly distributed in a sample volume with instantaneous displacement

\[
\bar{d}(r, \psi, \varphi, t) = [d_1(t)] \hat{e}_x + [d_\varphi(t)] \hat{e}_\varphi + [d_\psi(t)] \hat{e}_\psi \quad (1a)
\]

around their mean positions \( \bar{r}_s = [\bar{r}_x] \hat{e}_x + [\bar{\varphi}] \hat{e}_\varphi + [\bar{\psi}] \hat{e}_\psi, \quad s = 1, \ldots, S \), where \((\hat{e}_x, \hat{e}_\varphi, \hat{e}_\psi)\) denote the unit direction vectors in spherical coordinates. For a sample volume in tissue, the displacement is primarily due to cardiac pulsation, breathing and other tissue movement (clutter motion) relative to the transducer, \( \bar{d}^{\text{vib}}(r, \psi, \varphi, t) \). In addition, if the scatterers in the sample volume are vibrating with instantaneous displacement \( \bar{d}^{\text{vib}}(r, \psi, \varphi, t) \), then the combined displacement is:

\[
\bar{d}(r, \psi, \varphi, t) = \bar{d}^{\text{vib}}(r, \psi, \varphi, t) + \bar{d}^{\text{clutter}}(r, \psi, \varphi, t). \quad (1b)
\]

In color-flow (CF) and Doppler modes, an ensemble of \( E \) US pulses is transmitted in the same direction at a rate known as the pulse-repetition frequency (PRF). Then, the complex received signal from the \( m \)th pulse transmission, \( y(\tau, m) \), can be modeled as (Jensen 1991):

\[
y(\tau, m) = \sum_s \alpha_s h_{pe} \left[ f_0 \left( mT_{PRF} \right), \tau - \frac{2(r_s - d(mT_{PRF}))}{c} \right] \times \bar{x}_0 \left( \tau - \frac{2(r_s - d(mT_{PRF}))}{c} \right) e^{j2\pi f_0 \left( mT_{PRF} \right) \tau} + n(\tau, m), \quad (2)
\]

where \( T_{PRF} \) is the pulse-repetition interval, \( f_0 \) is the center frequency of the transducer, \( c \) is the speed of sound, \( h_{pe}(\cdot) \) is the pulse-echo spatial impulse response of a single point scatterer, \( \bar{x}_0(\cdot) \) is the temporal response of the transducer, and \( n(\tau, m) \) is thermal and electronic noise. It can be seen that both the envelope and phase of the complex signal are modulated with the instantaneous radial displacement.

Further insight into the effect of vibrations on the received echo can be obtained with two simplifying assumptions. First, the scatterer displacement can be assumed to be small compared to the spatial extent of the pulse-echo spatial impulse response and the envelope of the transducer response, so the “slow” time variations in the terms in braces in eqn (2) may be neglected (Heimdal and Torp 1997; Yamakoshi et al. 1990). Second, the displacement due to cardiac pulsation and vibrations near
A vessel wall may be assumed to be in the same direction radially outward from the vessel wall. Then, eqn (2) can be simplified to:

\[ y(\tau, m) = A(\tau)e^{2\pi j f_{\text{vib}}mT_{\text{PRF}}} + n(\tau, m), \quad (3) \]

where \( A(\tau) \) is the complex amplitude of the scattered signal. It is seen that the complex received signal is phase-modulated with the instantaneous displacement. For a radial simple harmonic vibration with peak displacement \( d_{\text{p}} \), frequency \( f_{\text{vib}} \), and constant-velocity tissue motion with velocity \( v_{\text{tiss}} \), the phase-modulated echo in eqn (3) can be expanded in a Bessel series as follows (Yamakoshi et al. 1990):

\[ y(\tau, m) = A(\tau)\left\{ \sum_{n=-\infty}^{\infty} J_n(\beta)e^{2\pi j f_{\text{vib}}mT_{\text{PRF}}} + jn\pi \right\} + n(\tau, m) \]

\[ = A(\tau)\left\{ J_0(\beta)e^{2\pi j f_{\text{vib}}mT_{\text{PRF}}} + J_1(\beta)e^{2\pi j (f_{\text{vib}}+1)mT_{\text{PRF}}} \right. \]

\[ - J_1(\beta)e^{2\pi j (f_{\text{vib}}-1)mT_{\text{PRF}}} + \cdots \right\} + n(\tau, m) \quad (4a) \]

where \( J_n(\beta) \) is the Bessel function of the first kind, \( \beta = \frac{4\pi f_{\text{vib}}d_{\text{p}}}{c} \) (4b) and \( f_{\text{vib}} = \frac{2\pi v_{\text{tiss}}}{c} \). (4c)

Thus, the CF signal from a vibrating sample volume can also be modeled as a sum of complex exponentials embedded in noise.

For real-time tissue vibration imaging, the data-acquisition time is limited; thus, only a small number of temporal ensembles (typically 6 to 16) can be acquired from each sample volume. Conventional clutter filtering and spectral estimation techniques lack sufficient resolution to discriminate between the tissue vibrations and normal clutter from such a short temporal record. Parametric modeling utilizing the characteristics of the vibration signal in eqn (3) and eqn (4a) is better suited for this purpose. We have developed vibration imaging algorithms based on two models: 1. decomposition of the phase of the CF signal into dominant components to separate vibration from clutter and 2. decomposition of the complex CF signal into complex exponentials embedded in noise.

**Vibration imaging based on phase decomposition**

The steps of the vibration-imaging algorithm based on eqn (3) are described in Fig. 1a. Constant-velocity motion is suppressed by down-mixing with the estimated tissue velocity. The instantaneous scatterer displacement in eqn (3) can be estimated from the residual phase \( \varphi(k) \) of the CF signal after suppressing any constant-velocity motion and stationary components. To detect vibrations, any random variations in the phase due to noise and blood flow must first be suppressed. These incoherent variations in the phase are expected to have a larger spread in the eigenvalue spectrum of the residual phase compared with the coherent vibrations from tissue. To compute the eigenvalue spectrum, the correlation matrix of the residual phase, \( R_{\varphi\varphi} \), is first estimated using the modified covariance method (Marple 1987). Eigen decomposition of the correlation matrix, \( R_{\varphi\varphi} \), can be performed using the iterative QR factorization:

\[ R_{\varphi\varphi} = Q_1R_1 = Q_1(Q_2R_2Q_2^H) = \cdots = (\prod_{j=1}^{k} Q_j)R_k(\prod_{j=2}^{k} Q_j^H), \]

(5a)

where \( R_k \) are upper-triangular matrices and \( Q_k \) are orthonormal matrices (i.e., \( Q_kQ_k^H = I \)), with \( Q_k^H \) denoting the Hermitian conjugate of \( Q_k \). After the kth iteration, the columns of :

\[ Q = \prod_{j=1}^{k} Q_j \]

(5b)

converge to the eigen vectors of \( R_{\varphi\varphi} \) and the diagonal elements of \( R_k \) converge to the eigen values, \( \lambda_j \). One measure of the spread of the eigenvalue spectrum is the
fraction of the total signal energy contained in the $p$ dominant components,
\[
E_p = \frac{\sum_{i=0}^{p-1} \lambda_i^2}{\sum_{i=0}^{2p-1} \lambda_i^2}, \tag{5c}
\]
where $\lambda_i$ are the eigen values arranged in decreasing order of magnitude. Noise and blood flow will have a smaller fraction of the energy in the dominant components and can be suppressed using a threshold criterion, $E_p > E_{\text{threshold}}$. A coarse computationally efficient estimate of the frequency of the dominant components, $\hat{f}_\text{vib}$, can be obtained by counting the zero crossings, $N_{\text{zero}}$, in the residual phase. This estimate can be further refined by interpolating the residual phase to compute the mean period of oscillation. Vibrations are detected if at least one half of a cycle is contained in the dominant components within the temporal window of an ensemble, i.e., if:
\[
\hat{f}_\text{vib} > \frac{F_{\text{PRF}}}{2E}. \tag{5d}
\]
The vibration amplitude may be estimated by the variance of the residual phase (Huang et al. 1992). These estimators are defined as follows:
\[
\hat{f}_\text{phase} = \frac{N_{\text{zero}} \times F_{\text{PRF}}}{2E}; \quad \hat{\varphi}_\text{phase} = \frac{c}{4\pi f_0} \sqrt{\text{var}(\varphi(k))}. \tag{6}
\]
We will refer to these estimators as the zero-crossing frequency estimator and the phase-variance amplitude estimator.

Vibration imaging using estimation of complex exponentials in noise

The steps of the vibration imaging algorithm based on eqn (4a) are described in Fig. 1b. The correlation matrix of the complex CF signal is estimated using the modified covariance method, and the eigen decomposition of the correlation matrix is computed. The frequencies $f_{\text{tiss}}$, $(f_+ = f_{\text{tiss}} + \hat{f}_\text{vib})$ and $(f_- = f_{\text{tiss}} - \hat{f}_\text{vib})$ can then be estimated using the modified root-MUSIC method, described in detail elsewhere (Stoica and Moses 1997). Vibrations can then be detected using a matching peak criterion $|f_+ + f_- - 2f_{\text{tiss}}| < f_{\text{threshold}}$. Because:
\[
\left| \frac{J(\beta)}{J(\hat{\beta})} \right| \approx \beta, \tag{7a}
\]
the ratio of the power in the frequency peaks can provide an estimate of the vibration amplitude (Yamakoshi et al. 1990). Therefore, the vibration frequency and amplitude may be estimated from the power spectrum as follows:
\[
\hat{f}_\text{spectral} = \left| \frac{f_+ - f_-}{2} \right|; \quad \hat{\varphi}_\text{spectral} = \frac{c}{4\pi f_0} \sqrt{\text{var}(\varphi(k))}. \tag{7b}
\]
where $p_{\text{tiss}}$, $p_+$, and $p_-$ are the power corresponding to the frequency peaks, $f_{\text{tiss}}, f_+$, and $f_-$, respectively. We will refer to these estimators as the spectral frequency estimator and the power ratio amplitude estimator.

Validation using a simulation model

To evaluate the proposed vibration detection algorithms, we developed a simulation model of vibrations in a blood vessel wall using the signal model described in eqn (2). The schematic of the model is shown in Fig. 2a. The US simulator Field II (Jensen 1996) was used to compute the pulse echo spatial impulse response, $h_{\text{pe}}(\cdot, \cdot)$, and the transducer temporal response, $x_{\text{td}}(\cdot)$. The scattering amplitudes, $\alpha_r$, and mean positions, $\vec{r}_r$, were randomly assigned from a Gaussian distribution with the scattering strength from the vessel wall 40 dB higher than that from blood. The instantaneous scatterer positions, $\nu(\vec{r}, t)$, were estimated using the phase of the Doppler US signal from the vessel wall of a normal human femoral artery, as shown in Fig. 2b. The motion was in a direction perpendicular to the vessel wall with the peak displacement of 0.08 mm. Vibrations were generated in one region of the vessel wall, with motion in a direction perpendicular to the vessel wall, with the peak amplitude of 5 $\mu$m and the frequency of 100 Hz. The clutter motion with vibrations is shown in Fig. 2b. The vibration, $\hat{d}_r^b(t)$ in eqn (1b), was modeled as a Gaussian-weighted sinusoid with additive white Gaussian noise at different signal-to-noise ratios (SNR), as follows:
\[
\hat{d}_r^b(t) = a_0 \sin(2\pi f_{\text{vib}} t)e^{i(\varphi(t) - \varphi_0)}. \tag{8}
\]
where $t_{\text{position}}$ and $t_{\text{duration}}$ are the position and duration of
the vibration in the cardiac cycle, $\beta_{SNR}$ is the SNR of the white Gaussian noise $n(t)$. The addition of Gaussian noise simulates broadband vibrations expected to be produced by blood flow eddies and turbulent flow. The vibration frequency was 100 Hz and $\beta_{SNR}$ was varied from 0 to 2.

Signals from blood were considered to be part of the noise spectrum in both our proposed algorithms. To further validate that signals from flow would not be falsely detected as vibrations, we also simulated blood flow in our model. The motion of scatterers corresponding to blood were generated using the model of flow in a human femoral artery proposed by Jensen (1996). The flow is parabolic with a peak velocity of 50 cm/s and the time-varying velocity profile as shown in Fig. 2c.

The Field II simulation parameters are described in Table 1. The simulated radiofrequency (RF) lines obtained were demodulated to obtain the in-phase ($I$) and quadrature ($Q$) data, and these were decimated to obtain the raw CF data. The vibration detection performance was evaluated with different threshold values to measure the sensitivity and specificity. For the phase-decomposition algorithm, the threshold value, $E_{thresh}$, indicates the % of energy in the dominant components for a signal to be considered as vibrations. For the root-MUSIC-based algorithm, the threshold value, $F_{thresh}$, indicates the maximum difference in frequency of a matching pair of complex exponentials. Simulations were performed with different threshold values and different model orders, and receiver-operating characteristic (ROC) curves were generated to evaluate the detector performance. The ROC curves can then be used as a guideline for choosing the appropriate threshold setting and model orders. For the phase-decomposition algorithm, the $p$th order model had a $2(p + 1) \times 2(p + 1)$ correlation matrix, with $2 \leq p < E/2$ for an ensemble size of $E$. Two dominant components were considered for vibration detection. For the root-MUSIC algorithm, the model order $p$ was chosen so that $3 \leq p < E/2$ to enable detection of a matching pair of exponentials and the estimated correlation matrix size was $2p \times 2p$ (Stoica and Moses 1997).

**Tissue vibration imaging system**

For tissue vibration imaging to be clinically useful, real-time visualization of vibrations is essential. Previously, we developed a programmable US signal and image-processing system using a new generation of high-performance multimedia processors to support all the conventional processing modes, such as B, M, color flow, and Doppler in software (Sikdar et al. 2003; Shamdasani et al. 2004). The main strength of a programmable system is the ease of development of new modes and applications without the need for new hardware or hardware modifications to conventional US machines. This programmable US machine allowed us to access and process the internal raw CF and pulsed-wave (PW) Doppler quadrature data. We have implemented our phase-decomposition algorithm for tissue vibration imaging in real-time.

**Experimental validation**

A schematic of the physical phantom (JJ&A Instruments, Duvall, WA) used for validating our vibration-imaging algorithms is shown in Fig. 3. A piezoelectric plate was vibrated at frequencies between 100 Hz and 800 Hz using a sinusoidal signal from a function generator. The amplitude of the vibrating plate was calibrated using a fiber optic position sensor (Plett 2000) for different drive voltages corresponding to peak plate displacements of 1 to 7 µm. This vibrating plate was immersed in a water bath and was imaged using the programmable US system with a 5-MHz linear transducer and an ensemble size of 10 at different PRFs.

**In vivo case studies**

To study the characteristics of pathologic tissue vibrations in vivo, data were collected from a patient with
a stenosed bypass vein graft in the femoral artery, following a protocol approved by our institution’s Human Subjects Review Committee. The programmable US machine was used for real-time imaging and data collection. Data were also collected from the punctured femoral artery of an anesthetized pig, following a protocol approved by the University of Washington Institutional Animal Care and Use Committee. The femoral artery of the animal was punctured percutaneously with a Doppler-guided needle by a veterinary surgeon, and real-time tissue vibration imaging was performed. To study organ bleeds, the spleen was surgically exposed and incised, and imaging was performed through a gel stand-off. For all the experiments, a 5-MHz linear probe was used for imaging and data collection with the PRF of 500 Hz and ensemble size of 10 in CF mode and PRF of 8 kHz in PW Doppler mode.

RESULTS

Simulation results

A vibration amplitude image is shown in Fig. 4a. Vibrations are overlaid on the B-mode image using a black-green colormap. The colormap is calibrated according to the values of the estimated amplitude. To quantitatively evaluate the proposed algorithms, two masks were generated, as shown in Fig. 4b: V corresponding to regions where vibrations were simulated and NV corresponding to regions where no vibration was present. Because the scatterers have a time-varying motion, the masks are appropriately generated spatially to ensure that no vibrating scatterers are present in the region NV. The percentage of pixels correctly detected as vibrations in the region V are counted as true-positives, and the percentage of pixels detected as vibrations in the region NV are counted as false-positives.

Fig. 4. (a) Vibration amplitude image of simulation model. (b) Masks used for computing the sensitivity and specificity of vibration detection.

The sensitivity, specificity and ROC curves for the two algorithms using different model orders are shown in Fig. 5. It can be seen from Fig. 5a that, for the phase-decomposition algorithm, the sensitivity decreases with the increasing threshold value for all model orders because more true vibrations are rejected with larger threshold values. Lower model orders have higher sensitivity. This is because the correlation matrix is smaller; thus, a better estimate can be obtained using the limited number of temporal samples. Figure 5b shows that the specificity is quite similar for all the model orders and increases with increasing threshold value because a larger threshold leads to better noise rejection. Upon closer investigation, we determined that the majority of false detections occur when the blood flow velocity is low and the clutter-to-blood signal ratio is high. In such cases, the I-Q Doppler signals from blood can be almost.

Fig. 5. (a) Sensitivity vs. threshold, (b) specificity vs. threshold, and (c) ROC curve for phase-decomposition-based vibration detection. (d) Sensitivity vs. threshold, (e) specificity vs. threshold, and (f) ROC curve for root-MUSIC-based vibration detection.
indistinguishable from those of a small-amplitude tissue vibration. The ROC curves for different model orders are shown in Fig. 5c. According to Fig. 5c, it can be seen that a sensitivity of 96% and a specificity of 98% can be achieved with a second-order model. To choose an appropriate threshold value, an operating point is selected in the ROC curve. The corresponding threshold value can then be found from Fig. 5a or b.

It can be seen from Fig. 5d that, for the root-MUSIC-based algorithm, the sensitivity increases with the increasing frequency threshold value for all model orders because more true vibrations can be detected if the frequency threshold is increased. Figure 5e shows that the specificity decreases with increasing threshold values because more false detections occur with increased frequency threshold. The fourth-order model has slightly better sensitivity and specificity due to better modeling of the clutter space. The ROC curves for the root-MUSIC-based algorithm are shown in Fig. 5f. For the third-order algorithm, a sensitivity of 97% and a specificity of 98% could be achieved, whereas, for the fourth-order algorithm, the sensitivity could be increased to 98% with a specificity of 99%.

The variation in the sensitivity with increasing vibration band width is shown in Fig. 6. It can be seen that all the algorithms can achieve similar sensitivity when the vibration is narrowband \((\beta_{\text{SNR}} = 0)\). As the vibration band width is increased, the sensitivity decreases for the root-MUSIC algorithm because it is based on modeling the vibrations as complex exponentials with narrow band width. On the other hand, the phase-decomposition algorithm is more robust to the vibration band width because it makes no \textit{a priori} assumptions about the vibration band width characteristics.

**Experimental results**

The vibration amplitude and frequency images of the plate phantom are shown in Fig. 7a and b, respectively. Vibrations have been correctly detected at the location of the piezoelectric plate. Because the edges of the plate are attached to the base, the maximum vibration amplitude is expected at the center of the plate, with zero displacement at the edges. This can be observed in Fig. 7. The estimated vibration frequency at the center of the plate is between 450 and 500 Hz. The MUSIC pseudospectrum is shown in Fig. 7c. The zero-frequency peak corresponds to stationary echo. A prominent double-sided peak is observed at \(\pm 500\) Hz, corresponding to the vibration frequency of the plate.

Figure 8a shows the ultrasonically estimated vibration amplitude (y-axis) vs. the independently measured values using the fiberoptic position sensor (x-axis) for
different drive voltages to the piezoelectric plate. The amplitude and frequency were estimated using the estimators defined in eqns (6) and (7b). The fiberoptic amplitude measurements were made at the center of the plate. Figure 8b shows the ultrasonically estimated frequency (y-axis) vs. the function generator frequency (x-axis). The solid line with a slope of unity is shown in both plots. The difference between the estimated and measured values is plotted against the corresponding measured value in Fig. 8c for amplitude and, in Fig. 8d, for frequency. As can be seen, the maximum difference between the detected and measured values is less than 1 \( \mu \)m for amplitude and less than 50 Hz for frequency for both estimators. Some of the differences in amplitude can be attributed to variability in the location on the plate at which the fiberoptic measurements were made.

**In vivo vibrations in human bypass vein grafts**

The color power image and the vibration image from a stenosed vein graft are shown in Fig. 9a and b. An arrow indicates the location of the stenosis. A perivascular artefact is visible in the color power image, but the vibration image clearly shows the origin of the bruit downstream of the stenosis. The vibration amplitude is highest close to the vessel wall and decreases farther away from the vessel wall. To evaluate the vessel wall displacement in more detail, a Doppler sample volume was placed at the location of the peak vibration amplitude and the displacement was estimated from the phase of the Doppler signal. The instantaneous position of the vessel wall and the corresponding spectrum are shown as a function of time in Fig. 10a and b. The displacement spectrum in Fig. 10b shows significant energy up to 200 Hz and repeats with each cardiac cycle. A cross-section of the spectrum is shown in Fig. 10c. A peak is observed at the break frequency (indicated by an arrow) beyond which the energy decays with increasing frequency. Figure 10d shows the pseudospectrum estimated from only 10 ensembles of CF data at the same location using the MUSIC algorithm. A prominent spectral peak is observed at the break frequency. It should be noted that the MUSIC pseudospectrum does not reflect the full spectral characteristics, but may be used to estimate the spectral peaks. This case study shows that in vivo tissue vibrations caused by blood flow eddies can be detected using only a short temporal record, demonstrating the feasibility of real-time vibration imaging.

**In vivo vibrations from arterial and organ bleeding in an animal model**

The color-flow image of the punctured femoral artery is shown in Fig. 11a. The dotted box indicates the region-of-interest (ROI). The arrow indicates the approximate location of the puncture. The vibration amplitude image is shown in Fig. 11b. Vibrations indicated in green are observed in the region of the puncture. The color Doppler image of the incised spleen is shown in Fig. 12a. The pooling blood from the incision accumulated between the organ and the gel stand-off is indicated by an arrow. Some flow is observed at the bleeding site, as indicated by the arrow. The vibration amplitude image is shown in Fig. 12b. Vibrations indicated in green are clearly observed at the bleeding site. The vibration frequency image in Fig. 12c shows low-frequency vibrations around 30 to 60 Hz.
Computational requirements

The computational requirements for the two proposed algorithms for different model orders are shown in Table 2. The required number of basic operations was estimated for real-time imaging at 10 frames/s with 32 scan lines, 256 samples per scan line and ensemble length of 10. The root-MUSIC-based algorithm requires eigen decomposition; thus, it has a high computational requirement, whereas the phase-decomposition method is significantly less computationally intensive because it involves operations on real signals only. The third-order phase-decomposition algorithm requires about 181 million operations/s as compared to 89 million operations/s required for color-flow imaging using the conventional autocorrelation algorithm under the same conditions (Shamdasani et al. 2004).

We have already integrated our phase-decomposition algorithm into our software-programmable US system for online visualization of vibrations during 2-D US scans. Currently, we are able to perform tissue vibration imaging at 9.1 frames/s for 32 scan lines with an ensemble size of 10 and 256 samples per scan line. The computational power of US machines has increased significantly in recent years, benefiting from advances in processor technology (Sikdar et al. 2003), and this trend is expected to continue in the future. Many modern processors targeted for multimedia applications have specialized instructions that can perform complex multiplications and additions with the same computational overhead as real multiplications and additions. On these processors, the computational burden to support our algorithms can be reduced by a factor of three or four. Thus, the additional computational burden of our proposed tissue-vibration imaging algorithms can be reasonably supported in modern US machines.

DISCUSSION

Detectable vibration amplitudes and frequencies

In phantom experiments, we have accurately detected vibrations with a peak amplitude of 1 μm. The
minimum detectable vibration amplitude depends upon the noise level and dynamic range of the phase of the received US echo. In modern US machines, the phase can have a dynamic range of 96 dB or more (for 16-bit quadrature demodulated data), and the signal-to-electronic and thermal noise level is typically 80 dB or more. Therefore, from eqn (6), vibrations as small as 50 nm may theoretically be detected using US (Plett 2000).

Practically, attenuation of the US signal will reduce the dynamic range and limit the minimum detectable amplitude in deep tissue to around 0.5 μm (Walker and Trahey 1994).

The detectable vibration frequencies depend upon the choice of PRF, \( F_{\text{PRF}} \). A PRF that is too low compared to the vibration frequency would lead to aliasing, and too high a PRF will fail to detect low-frequency vibrations. A vibration can be detected only if at least a half of one vibration cycle is captured within the temporal window corresponding to an ensemble. Thus, for an ensemble size \( E \), all vibrations with frequency \( f_{\text{vib}} \) such that

\[
\frac{F_{\text{PRF}}}{2} \times E \leq f_{\text{vib}} < \frac{F_{\text{PRF}}}{2},
\]

can be detected theoretically without aliasing. Because vibrations can be broadband, a high-frequency vibration interrogated at a low PRF value can be mistaken for noise using our algorithm. Thus, for better sensitivity, it is desirable to have a PRF and an ensemble size such that only a few periods of the vibration are included in an ensemble. Thus, the maximum detectable frequency \( f_{\text{vib}}^{\text{max}} \) is:

\[
f_{\text{vib}}^{\text{max}} = k \frac{F_{\text{PRF}}}{E},
\]

when \( k \) periods of the vibration are included in an ensemble. Our simulation and phantom experiments indicate that reliable detection may be performed with one half to six vibration periods during the interrogation period. For example, with a PRF of 1 kHz and an ensemble size of 16, vibrations with frequency between 31.3 Hz and 375 Hz may be reliably detected.

**Sources of artefacts**

In color-flow acquisition, interrogation along each scan line is performed for only a brief period of time. Vibrations are transient, with typical durations of 10 to 100 ms; thus, there is a possibility that some vibrations may not be interrogated. Because the vibrations typically have a relatively large spatial extent and repeat every cardiac cycle, it is unlikely that the vibrations will be missed entirely. However, the spatial extent of the vibrations visible in the image may be only a part of the true spatial extent. By appropriately choosing the PRF and the ROI, such discrepancies may be minimized.

Other artefacts may be falsely detected as vibrations. Transducer motion may introduce additional frequency peaks in the clutter spectrum and may cause false detections. However, these may be minimized when a trained sonographer performs the scanning. Vibrations in the tensed skeletal muscle of the sonographer (Heimdal

---

Table 2. Computational requirement (million operations/s) for real-time imaging at 10 frames/s with 32 scan lines, 256 samples/scan line and ensemble 10

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>( p = 2 )</th>
<th>( p = 3 )</th>
<th>( p = 4 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Root-MUSIC</td>
<td></td>
<td>3631</td>
<td>7653</td>
</tr>
<tr>
<td>Phase decomposition</td>
<td>181</td>
<td>489</td>
<td>1107</td>
</tr>
</tbody>
</table>

---

Fig. 11. (a) Color flow, (b) vibration amplitude and (c) vibration frequency image of a punctured femoral artery. The arrow indicates the puncture site. Localized vibrations are observed around the puncture site.

Fig. 12. (a) Color power image of incised spleen imaged through a gel stand-off; the bleeding site is clearly visible. Accumulated blood from the bleeding site is pooled between the stand-off and the spleen. (b) Vibration amplitude image showing vibrations surrounding the bleeding site. (c) Vibration frequency image showing low-frequency vibrations.
and Torp 1997) and any ambient vibrations may be detected in the vibration image. In addition, the root-MUSIC method may produce spurious peaks that can be falsely detected as vibrations. Such artefacts can be easily distinguished from pathologic vibrations, which are expected to be correlated with the anatomy and periodic with every cardiac cycle. Because vibrations are expected to have spatial coherence, utilizing multiple axial sample volumes for estimating the correlation matrix can improve specificity. These artefacts can be also avoided if additional temporal samples are available. Any vibrations displayed in the vibration image should, therefore, be confirmed with the vibration spectrum by placing a Doppler sample volume at the location of the peak intensity.

Clinical applications
Tissue vibration imaging could be clinically useful for the assessment of stenoses and other vascular abnormalities traditionally associated with bruises that are otherwise hard to diagnose using conventional duplex US. Our ultrasonic vibration imaging technique is attractive because of its potential to visualize small-amplitude vibrations at their origin. The vibration spectra can be used to compute the break frequency, which is directly related to the residual lumen diameter at the stenosis. An important application of tissue vibration imaging could be in the noninvasive diagnosis of coronary artery stenoses. Conventional duplex US is limited by the difficulty in visualizing coronary arteries and the poor scattering strength from coronary blood flow. Patients with coronary artery stenosis have diastolic murmurs with frequencies between 300 Hz and 800 Hz (Akay et al. 1993). Thus, clinically significant coronary artery stenoses would be expected to create diastolic vibrations with amplitude and frequency dependent on coronary flow rate and minimum residual lumen diameter. Diastolic-gated transthoracic imaging of the vibrations can complement duplex US as an inexpensive and effective method for diagnosing clinically significant coronary artery stenoses. Of course, this possibility requires further study and thorough clinical testing.

Another useful clinical application of tissue vibration imaging can be in the localization of active internal bleeding. Internal bleeding is a significant cause of death in cases of trauma, and rapid and effective diagnosis of patients with uncontrolled bleeding is important to lower mortality and morbidity. B-mode US is often used to visualize intracavitary free fluid due to bleeding. Previously, the use of Doppler US has been shown to be effective for locating active bleeding sites (Martin et al. 1999), but suffers from the disadvantage of a limited ROI, slow velocities from organ bleeding and poor echo strength from deep bleeds. Our preliminary results indicate that vibrations are produced due to arterial bleeding at the bleeding site, and it is possible to detect and image these vibrations using our algorithm. Thus, tissue vibration imaging could be an attractive approach for rapid localization of active bleeding sites in a large ROI. The vibration amplitude is expected to be the largest near the site of the bleeding and can be used to localize the bleeding site quickly and noninvasively. The vibration frequency could provide an indication of the bleeding rate. The strong backscattered ultrasonic echoes from tissue vibrations can improve visualization of active internal bleeding sites that are otherwise hard to image due to weak scattering from blood. Further studies are being performed to evaluate the effectiveness of tissue-vibration imaging for localizing internal bleeding sites using more animal experiments.

Potentially, this new tissue-vibration imaging technology could be useful in a variety of devices and clinical settings. For example, a low-cost screening device with tissue-vibration imaging functionality could be useful to paramedics and primary care practitioners for screening and monitoring patients. On the other hand, a tissue-vibration imaging mode on high-end cardiovascular US systems can augment duplex US for enhanced diagnostic capability.

CONCLUSION
We have demonstrated the feasibility of real-time US imaging of low-intensity local vibrations in the vessel wall and surrounding tissue associated with stenoses and arterial bleeding. We have developed algorithms based on parametric signal decomposition and spectral estimation for imaging small-amplitude tissue vibrations using only 10 temporal samples. Simulations show that these algorithms have high sensitivity (96 to 98%) and specificity (98 to 99%) for detecting vibrations in the presence of clutter as well as blood flow, and are robust even when broadband vibrations are present. The vibration amplitude and frequency can be estimated accurately. Real-time tissue-vibration imaging has been implemented on an US machine, and vibrations were observed in stenosed bypass vein grafts in a human subject and a punctured femoral artery and incised spleen in an animal model in preliminary in vivo experiments. In vascular diseases, tissue-vibration imaging could provide additional diagnostic information that is currently not available to the clinician using conventional tools. An US device with tissue-vibration imaging capability can become a useful screening and diagnostic tool, augmenting routine procedures such as auscultation and duplex US.

Acknowledgements—This research was partially funded by the Office of Naval Research, Code 341, (BOA N00014-01-G-0460), order
0003), and Hitachi Medical Corporation. The authors gratefully acknowledge the help provided by Dr. Daniel Leotta and Jean Primozich for the patient study and Dr. Frank Starr, III for the animal study.

REFERENCES


