Volume-specific parameter optimization of 3D local phase features for improved extraction of bone surfaces in ultrasound

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Abstract

Background Accurate localization of bone surfaces remains a challenge hampering adoption of ultrasound guidance in computer-assisted orthopaedic surgery. Local phase image features have recently been proven efficacious for segmenting bone surfaces from ultrasound images, but the quality of the processing depends on numerous filter parameters that are currently set through a trial and error process that is tedious, unintuitive and subject to large inter-user variability.

Methods A method is presented for automatically selecting parameters of Log-Gabor filters used to extract bone surfaces from 3D ultrasound volumes that is based on properties estimated directly from the specific image.

Results A 15% and 69% average improvement in bone surface localization accuracy on phantom and clinical data, respectively, is demonstrated compared with empirically-set parameters.

Conclusions These findings imply that Log-Gabor filter parameter optimization is necessary for accurate extraction of bone surfaces from ultrasound data.

Keywords 3D ultrasound; phase features; parameter selection; bone segmentation; orthopaedic

Introduction

Historically, the primary intraoperative imaging modality used in orthopaedic surgery is C-arm fluoroscopy, which uses X-rays to create two-dimensional (2D) projection images. However, numerous researchers have proposed that intraoperative ultrasound (US) could potentially be more effective than fluoroscopy in a variety of procedures (e.g. hip arthroplasty (1), pelvic fracture fixation (2,3), spine (4,5), femur fracture fixation (6), shoulder arthroplasty (7) and scaphoid fracture repair (8), among others) and could reduce or eliminate radiation exposure to the patient and surgical team (2). To be useful in such applications, it is often necessary for the image interpretation component of a surgical navigation system to be able to automatically and rapidly extract accurate bone surfaces from the US image set. However, this is difficult because US images have high levels of speckle and other artefacts that significantly complicate automatic image processing (9). The three-dimensional (3D) local geometry of the imaged bone as well as the US beam direction with respect to the targeted surface strongly influence the appearance of bone...
boundaries (9). Finally, bone boundaries have similar intensity profile as the soft tissue interfaces. Due to these difficulties, many early uses of US in orthopaedic surgery required manual identification of bone surfaces, often prior to registration with pre-operatively acquired computed tomography (CT) scans (2–4,8).

Several approaches have been proposed to automate bone segmentation process in US based on image intensity and gradient information (9–11). Unfortunately, due to the previously mentioned difficulties in US imaging these reported methods remain highly sensitive to variations in data and parameter settings. To improve the robustness of the segmentation, some researchers have proposed incorporating a priori bone models into the segmentation framework (11). However, bone fragments, as well as bones that have been reduced and secured with fixation devices, do not have continuous smooth surfaces and thus will not match intact bone models, which renders such methods difficult to use in many practical applications. Furthermore, most previously reported intensity and gradient-based methods have been developed for and applied only to 2D US images as opposed to 3D US volumes, which are increasingly available on newer US systems.

Recent developments in US technology, primarily due to advances in computer technology and computational techniques together with advanced probe design, have enabled 3D US to be efficiently and successfully used in a range of clinical procedures such as breast biopsy (12), echocardiography (13), and prostate brachytherapy (14). However, the possibility of using 3D US as an alternative to 2D fluoroscopy imaging for assessing fracture reduction and guiding surgical interventions in orthopaedic surgery is relatively under-explored. The main clinical application of interest to us is bone fractures. In 2005, fractures were the leading cause of hospitalization for injuries, accounting for 53% of all injury discharges in the United States (15). Acute management of fractures is complex and demands precise surgery to optimize post-operative function (15). This is especially important in distal radius and pelvic fractures. Distal radius fractures are responsible for about one sixth of all fractures seen in American emergency departments (16,17). In Canada, the National Trauma Registry recorded 109 738 major injuries in 1999, of which 4% corresponded to a pelvis fracture, which is often associated with severe bleeding and major intra-abdominal injuries (18). Over 40% of patients requiring pelvic stabilization suffer from long-term complications, usually neurological, urological and non-specific pain (18).

The use of intensity-invariant local phase based features has recently shown great promise in US image processing, particularly for accurate segmentation of soft tissue interfaces (19,20) and, more recently, bone boundary in 2D and 3D US data (21–23). However, the resulting segmentations are dependent on and sensitive to the choice of a number of key filter parameters. The manual process of empirically tuning the filter parameters through trial and error and ad hoc investigation of filter outputs on sample images (19,21) is tedious, unintuitive, and susceptible to large intra- and inter-user variations. Such tuning difficulties seriously limit the practical use of these methods by non-technical experts, particularly clinical users.

Prior studies have not investigated the effects of parameter selection on the accuracy of surfaces extracted from 3D data or provided guidelines for proper parameter selection. In (23), we proposed a preliminary framework for automating the selection of Log-Gabor filter parameters for 2D US images, which we validated on Sawbone artificial bone models and in vitro phantom setups only. In these settings, we showed a 35% improvement in accuracy of bone surface localization compared with 2D empirically-set parameterization (21). However, as shown in our previous work (22), 2D methods do not take advantage of the high correlations that exist between adjacent slices and are therefore subject to large spatial compounding errors (similar to registration and tracking errors introduced during compounding) as well as errors associated with US beam thickness effects.

In this work, therefore, we extend our automated filter parameter selection approach from 2D slice-based processing to a fully 3D volumetric analysis based on a phase scale-space framework employing volume projections, surface curvature measures and directional filter banks. Our optimization is directed towards the problem of imaging bone surfaces and hence exploits differences in the characteristics of bone boundary responses and speckle noise in US images. We present quantitative and qualitative validation on a carefully designed in vitro phantom as well as with a data set of 24 in vivo clinical scans obtained from 10 patients who suffered distal radius or pelvic fractures. Finally, we also show improvements achieved in terms of sensitivity to typical US artefacts. We compare the results to our previous empirically-set 3D parameterization approach (22) and 2-D automatic optimization approach (23).

Materials and methods

3D Local phase-based filter design

It is well known that local phase information can be obtained by convolving a signal with a pair of band-pass quadrature filters. A common choice of quadrature filter is the Log-Gabor filter which can be constructed with a wide bandwidth while still maintaining a zero DC component (24–26). The transfer function of the Log-Gabor filter is given as:

$$G_i(p,k,\omega_0) = \exp\left(-\frac{\log^2\left(\frac{\omega(p)}{\omega_0}\right)}{2\log^2(k_p)}\right).$$  \hspace{1cm} (1)$$

Here the subscript \(i\) denotes the scale of the filter. To obtain simultaneous localization of spatial and frequency information, analysis of the signal must be done over a
range of frequencies/scales. The scaling of the Log-Gabor function is achieved by using different wavelengths that are based on multiples of a minimum wavelength, $\lambda_{\text{min}}$, which is a user-defined parameter. We have in the past considered the possibility of using multiple spatial scales, but in practice we found that a single scale gave sufficiently good results with minimal computation time (23). In this study, therefore, we chose to restrict our filter sets to a single spatial scale characterized by $\lambda_{\text{min}}$. The relationship between the filter scale $i$, and the filter center frequency $\omega_0$ is set as $\omega_0 = \frac{1}{(\lambda_{\text{min}} \times (6)^{i-1})}$ where $\delta$ is a scaling factor defined for computing the center frequencies of successive filters. We have previously found that selecting a value of $\delta = 3$ provides good balance between accurate bone surface extraction in the presence of speckle and soft tissue artifacts across a wide range of images (21,23).

The azimuth ($\phi$) between the direction of the orientation of the 3D Gaussian spreading function for the predicted from the ratio of $\omega_0$ to $\delta$. The spatial bandwidth ($\beta$) of the filter is calculated from the ratio of $\kappa_{\beta}$ using the following formula:

$$\beta = -2 \times \left(\frac{2}{\log 2}\right)^{0.5} \times \log \left(\kappa_{\beta}\right)$$

(23, 24). The Log-Gabor filter is extended to 3D by multiplying the transfer function with a rotational symmetric angular Gaussian function ($A_j$) that controls the orientation selectivity of the filter (22, 27) which results in a 3D Log-Gabor filter (22, 27), $3DG_{ij}$, with a transfer function given as:

$$3DG_{ij} = G_i(p(\alpha_0)) \times A_j(p(\phi_j, \theta_j, \sigma_{\omega}))$$

$$= \exp\left\{-\frac{\log^2 \left(\frac{\omega(p)}{\omega_0}\right)}{2\log^2 \left(\kappa_{\beta}\right)}\right\} \times \exp\left\{-\frac{\alpha(p\phi_j, \theta_j)^2}{2\sigma_\alpha^2}\right\}$$

(2)

Here the subscripts ‘$i$’ and ‘$j$’ denote the scale and orientation of the 3D filter, respectively. The angle between the direction of the filter, which is specified by the azimuth ($\phi_j$) and elevation ($\theta_j$) angles, and the position vector of a given point $p$ in the frequency domain is given by $a(p, \phi_j, \theta_j) = \arccos(p \cdot v_j \left| \left| p \right| \right|)$, where $v_j = (\cos\phi_j \times \cos\theta_j, \cos\phi_j \times \sin\theta_j, \sin\phi_j)$ is a unit vector in the filter’s direction. $\sigma_\alpha$ is the standard deviation of the Gaussian spreading function in the angular direction that describes the filter’s angular selectivity; lower values for $\sigma_\alpha$ imply higher orientation selectivity.

Typical bone surfaces in US images appear as blurred line-like structures, with non-uniform intensity and substantial shadowing beneath the surface. Investigating a line profile across the bone surface reveals that the US response depicts a ridge-like edge rather than a step or ramp-like edge at the expected bone boundaries (21). We, therefore, use the outputs of the 3D Log-Gabor filter to construct a 3D ridge detector based on 3D phase symmetry (3DPS) (22). In our previous (22) work, the 3D Log-Gabor filter was constructed using empirical filter parameters.

In the following sections, we derive a data-driven approach that performs a volume-specific, automatic selection of all of the following filter parameters: spatial scale ($\lambda_{\text{min}}$), width of spreading function ($\kappa_{\beta}$), number of orientations ($j$), and, for each orientation, the triplet ($\phi_j, \theta_j, \sigma_\alpha$) = (azimuth ($\phi_j$) and elevation angles ($\theta_j$), and angular bandwidth ($\sigma_\alpha$)).

**Frequency bandwidth selection**

The filter bandwidth in the radial direction, $\beta = -2 \times \left(\frac{2}{\log 2}\right)^{0.5} \times \log (\kappa_{\beta})$, is related to both the speckle and bone boundary responses in the US image. We thus estimate the frequency bandwidth by analyzing the speckle size. Since the US images used in this study are B-mode images where the intensity is compressed on a logarithmic scale, we first map the intensity to a linear scale using $US_i(x,y,z) = 10^{\left(\frac{\log_{10}(x,y,z)}{51}\right)}$, where $US_i(x,y,z)$ is the decompressed grey level intensity of the voxel located at image coordinates $(x,y,z)$ and $US(x,y,z)$ is the measured intensity in the B-mode image volume (28, 29). The analysis is done as rays in the elevation direction for different scanning depths (in the conducted experiments, the transducer’s center ultrasound frequency was 7.5 MHz and image depth setting ranged between 1.9 cm and 7.2 cm). In order to isolate a region with fully developed speckle, the images are cropped so these regions containing shadow or other artefacts are excluded. The autocorrelation function is then computed for each cropped region and the speckle size estimated as the full-width at half-maximum (FWHM) of the autocorrelations. This value is then used as a measure of the speckle size similar to Wagner et al. (30). $\kappa_{\beta}$ is computed for each image as:

$$\kappa_{\beta} = e^{-\frac{r}{2 \times \text{FWHM} \times \sqrt{\log 2}}},$$

(3)

where $r$ is the pixel size in mm. Selecting a bandwidth significantly greater than this value (i.e. selecting a smaller value for $\kappa_{\beta}$) will result in a filter that fails to separate small scale speckle features from larger scale boundary responses. On the other hand, selecting a significantly lower bandwidth will reduce the accuracy of the boundary detection and cause blurring of the detected bone boundary (Figure 1).

**Filter orientation initialization**

The 3DPS metric is calculated by summing the responses of the 3D Log-Gabor filters tuned to a number of pre-set orientations (22). However, contributions from filter orientations that do not contain a strong bone response can add more noise than signal. Since the filter response is strongest when the orientation of the filter is perpendicular to the bone surface orientation, identifying and combining filter angles that are perpendicular to the bone can markedly improve the extracted bone features compared with less favourable filter orientations (23).

Bone responses in B-mode US images typically appear as elongated linear (2D) or planar (3D) objects of higher intensity value compared to other features such as elongated linear (2D) or planar (3D) objects of higher intensity value compared to other features such as elongated linear (2D) or planar (3D) objects of higher intensity value compared to other features such...
as soft tissue interfaces or speckle regions. We therefore expect the integral of intensity values to be high along lines or planes that are aligned with (tangent to) the bone surfaces. We therefore use the 3D radon transform (3DRT) to detect the orientation of the bone surfaces. A 3DRT represents a 3D volume as a collection of projections along various planes defined by the shortest distance, \( \rho \), from the origin, the azimuth angle, \( \phi \), around the \( z \) axis and the elevation angle, \( \theta \), around the \( y \) axis. To determine the initial filter angles, we apply a k-means clustering algorithm to a histogram of the intensity values from the 3DRT volume (i.e. we select a relatively small number of candidate center values evenly distributed across the intensity range. We typically set the number of cluster value \( k = 6 \), but results appear to be relatively invariant to this choice), assign intensity values to the nearest cluster center, re-compute the mean intensity for each cluster, and iterate until convergence. We then identify all regions in the clustered volume that contain voxels labelled with the highest intensity cluster (see red arrow in Figure 2) and compute the corresponding centroid as our initial estimate for the filter angle. In our applications (radial and pelvis fractures), the bone surfaces are usually either roughly cylindrical (e.g. long bones) or planar (certain views of the pelvis). For such surfaces, we have found that three filter orientations is almost always sufficient to capture the relevant detail. We therefore add two additional viewing angles oriented at \( \pm 1 \) standard deviation along the principal axis of the points belonging to the highest intensity cluster. These three initial angles are used as the initial filter angle parameters during

Figure 1. 3D Log-Gabor filter frequency bandwidth selection. The images show selected coronal and sagittal planes from the volumetric data set for better visualization. (a) 3D in vivo B-mode US volume obtained by scanning a human subject from iliac crest region. (b) 3DPS volume obtained using a 3D Log-Gabor filter with a frequency bandwidth value of \( \kappa \beta = 0.05 \). Selecting a small filter scale results in the extraction of speckle and soft tissue features (red arrows) together with the bone surfaces (white arrow). (c) 3DPS volume obtained using a 3D Log-Gabor filter with a frequency bandwidth value of \( \kappa \beta = 0.75 \). Selecting a larger filter scale results in the extraction of blurred bone surfaces (white arrows) together with blurred soft tissue interfaces (red arrows). (d) 3DPS volume obtained by selecting an appropriate bandwidth (\( \kappa \beta =0.27 \)) where the 3DPS captures continuous sections of the bone with minimal influence from soft-tissue interfaces and speckle
the calculation of the filter scale, as explained in the next section.

**Filter scale selection**

Since bone surfaces in US typically appear as elongated line- or plane-like objects, our scale selection employs a multi-scale eigenvalue analysis of the Hessian matrix (4) (31):

$$H(x,y,z) = \begin{bmatrix} Lxx & Lxy & Lxz \\ Lyx & Lyy & Lyz \\ Lzx & Lzy & Lzz \end{bmatrix}, \text{with } L_{\text{sp}} = \frac{\gamma^2}{\delta_{\alpha\beta}}L. \quad (4)$$

Here \( L \) is the US volume convolved with a 3D Log-Gabor filter at a particular scale \( (\lambda_\text{min}) \), and \( \alpha \) and \( \beta \) represent the spatial derivatives. Since our main interest here is localizing bone contours, which generally appear as ridges in US images, we employ a metric that captures the ‘ridge-ness’ content in the volume, which we define as:

$$3DRS_i = t^3 \times (K_1 - K_2)^2. \quad (5)$$

Here, \( t \) is the scale of the filter \( (t = \lambda_\text{min}) \), and the principle curvatures are defined as:

$$K_1 = \text{Trace} \left( H(x,y,z) \right) + \sqrt{\text{Trace}(H(x,y,z))^2 - 4 \times \text{det}(H(x,y,z))}, \text{ and}$$

$$K_2 = \text{Trace} \left( H(x,y,z) \right) - \sqrt{\text{Trace}(H(x,y,z))^2 - 4 \times \text{det}(H(x,y,z))}. \quad (6)$$

\( \gamma \) is a normalization constant that is related to the dimensionality of the image feature (32). The analysis is performed over different scales and the scale that maximizes the ‘ridge-ness’ in the 3D Log-Gabor-filtered image (defined as the sum of the intensity values in \( 3DRS_i \)) is chosen to be the optimal filter scale (Figure 3 (a)). At that optimal scale the response of the filter produces a sharp elongated ridge feature (Figure 3 (b)) aligned with the bone surface, whereas significantly different scales will result either in detection of speckle (Figure 3(c)) or loss of bone surfaces (Figure 3(d)). The filter scale selection analysis is repeated for each initial filter orientation separately.

**Filter orientation refinement**

Since B-mode US volumes are used as an input to the 3DRT during the Filter Orientation Initialization stage, any soft tissue interfaces (ie. muscle tissue interface) that resemble bone surfaces and are present in the US volume will have an effect on the calculated filter orientations. In order to reduce this effect and further refine the filter angles to determine the final filter orientations, the 3DRT is recalculated for the ridge strength image \( 3DRS \), obtained using the scale and initial filter orientation calculated in the Filter Orientation Initialization and Filter Scale Selection sections, respectively. Figure 4 shows an example of the 3DRT calculated from the \( 3DRS \), volume obtained using a filter scale value \( \lambda_{\text{min}} = 25 \) and an initial filter orientation of \( (\theta_{3DRT} = 144^\circ, \ \psi_{3DRT} = 92^\circ) \). Since the strongest filter response will belong to the bone surface,
The filter angular selectivity of the filter is controlled by the angular bandwidth parameter, $\sigma_\alpha$. For large angular bandwidths, the filter acts as a smoothing filter with little orientation sensitivity, whereas for small angular bandwidths, the filter behaves more as a line detector. This makes the extracted features look like short line segments when the true surface is curved. To select the optimal bandwidth, we analyse the kurtosis of the 3DRT of 3DRS, as a function of the angular bandwidth. This measure has previously been used as a sharpness metric (33). The optimum angular bandwidth is thus chosen as the one maximizing the kurtosis (23). When the edge sharpness degree is higher, the kurtosis value is larger and image definition is better (i.e. a 3DRS image with uniform black background with sharp high intensity bone boundary). In contrast, a small kurtosis value indicates that the edge is more blurred and image definition is worse (i.e. a 3DRS image with uniform black background degraded with speckle/soft tissue interfaces or short line

**Figure 3. Filter scale selection.** (a) Filter scale versus sum of intensity values of 3DRS. (b)–(d) 3DRS images calculated from the US volume shown in Figure 2(a) using scales (b) $\lambda_{\min} = 25$ (obtained from the max value of the plot in (a) shown in straight vertical line), (c) $\lambda_{\min} = 5$ (d) $\lambda_{\min} = 140$. At the optimal filter scale ($\lambda_{\min} = 25$ for this example) the response of the filter produces a sharp elongated ridge feature (b), whereas significantly different scales will result either in detection of speckle (c) or loss/blurred bone surfaces (d).

**Figure 4. Final orientation selection.** (a) 3DRS image calculated using filter scale value $\lambda_{\min} = 25$ and initial filter orientation ($\phi_{3DRT1} = 144^\circ$, $\theta_{3DRT1} = 92^\circ$). (b) 3DRT of Figure 4(a). The maximum value of the resulting 3DRT is chosen as the final filter orientation. The initial filter angle is updated to ($\phi_{3DRT1Final} = 133^\circ$, $\theta_{3DRT1Final} = 90^\circ$)
segments with different intensity values). During this stage, the 3DRS, images are obtained using the optimum filter scale as calculated in the Filter Scale Selection section.

Experiments and validation

Phantom specimen

In order to evaluate the accuracy of our 3D phase symmetry technique with automatic parameter selection, we compared performance of this method on a bovine bone phantom with both 2D and 3D versions of the phase symmetry technique. The phantom consisted of a bovine femur with soft tissue overlaid. The bone was supported by a firm gel (Super Soft Plastic, M-F Manufacturing, Texas, USA) in which 28 fiducials (1 mm diameter steel balls) were added to the construct with 14 balls placed on each side of the bone (longitudinally), spaced at equal axial intervals over a distance of 75 mm. The difference in the speed of sound in soft tissue (est. 1540 m s\(^{-1}\)) and gel (est. 1340 m s\(^{-1}\)) during the image reconstruction process was compensated to improve the accuracy of alignment of the ultrasound and CT (22,23). We obtained axial US scans of this specimen, with each volume spanning a 12 mm long region (Figure 5). The phantom was scanned with both an Xtreme CT machine (HRpQCT, XtremeCT; Scanco Medical, Switzerland) with isometric 0.25 mm voxels and a GE Voluson 730 Expert ultrasound machine (GE Healthcare, Waukesha, WI) with a 3D RSP5-12 transducer. The dimensions of the US volumes collected were 199 × 119 × 60 (lateral × axial × elevational) with an isotropic resolution of 0.2 mm. In total, 25 different US scans were obtained by withdrawing and reapplying the US transducer each time (so that the scans were slightly different each time) and in each case making sure the full length of the bovine setup was covered. The CT and US data sets were registered using a fiducial-based rigid registration method using the AMIRA software (TGS, San Diego, CA, USA). This fiducial-based registration method minimizes the sum of the squared distances between the corresponding fiducial points identified in both data sets. The 1 mm diameter fiducials were manually selected by an operator from both data sets (US and CT). The voxel with the highest/brightest intensity response was chosen as the top of the fiducial from US volumes. For selecting the fiducials from CT scans the operator selected the top of the fiducial rather than the middle. The accuracy of the fiducial based registration was assessed by calculating the fiducial registration error (FRE). Bone surfaces were extracted from the CT volumes using a threshold that minimized intra-class variance (34). Previously, we investigated the effect of the thresholding method on the resulting gold standard bone surface from CT, where we tested eight different
automatic threshold selection methods (22). We showed that the variability induced by using different thresholds was low – in the range 0.04 mm to 0.1 mm – so we believe that the choice of threshold value has little impact on the accuracy results reported in this study (22).

To perform quantitative comparisons, US scans were processed to extract the bone surfaces using the empirical 3D Log-Gabor filter parameters reported in (22) (3D + E), the 2D optimized parameters reported in (23) (2D + O) and our proposed 3D optimized parameters (3D + O). The accuracy of the resulting surface matching (bone surface localization error (SLE)) was evaluated by computing the root mean square (RMS) distance between the surfaces extracted from the CT by thresholding and US images by local phase image processing using the proposed and previously reported PS methods, respectively.

In order to quantify the improvement in terms of sensitivity to typical US artefacts, we also calculated an image surface quality metric $Q$ (see Equation (7)), which represents an intensity-weighted measure of the average signed distance to the surface identified on the phase-processed US image:

$$Q = \frac{\sum_{x,y,z} d_s(x,y,z) \times I(x,y,z)}{\sum_{x,y,z} I(x,y,z)},$$

where $d_s(x,y,z)$ and $I(x,y,z)$ are the signed distance and 3DPS intensity value, obtained using the proposed method and the previously published methods ((3D + E) (22) and (2D + O) (23)), at pixel location $(x, y, z)$, respectively. The closer $Q$ is to zero, the better the quality of the extracted bone surface.

Clinical data
After obtaining all required ethics board approvals, we obtained both CT and US scans from 10 consenting patients who had been admitted to Vancouver General Hospital (Vancouver, BC, Canada) (a Level 1 Trauma Center) with radius (four patients) or pelvic fractures (six patients) that required a CT scan as part of normal clinical care. The CT images provided the ‘gold standard’ surface for comparison with the surfaces extracted from US images. Dorsal, volar, and radial views were obtained in the case of radial fractures and iliac crest/iliac fossa views in the case of pelvic fractures. Since no fiducials were available in the clinical study, a manually-supervised anatomical landmark-based registration method was used to bring the two volumes into an initial alignment using the AMIRA software (TGS, San Diego, CA, USA). After extracting bone surfaces from both volumes this initial registration was then further optimized using a surface-based registration method (35). The quantitative validation was assessed by measuring the RMS distance between the extracted surfaces (bone surface matching error (SME)).

Results
The optimal filter frequency bandwidth was calculated as $\kappa = 0.27$ and the value $\gamma$ was set to 0.75 since this was reported to be optimal value for ridge feature detection (32).

Qualitative results for phantom study
Figure 6 shows qualitative results obtained from the phantom study. The yellow surface is the ‘gold standard’ surface extracted from the CT scan. Subjectively, it appears that the 3D + O method is less sensitive to soft tissue interfaces and typical US artefacts.

Qualitative results for clinical study
Figure 7 shows qualitative results obtained from clinical scans of in vivo fractured distal radius and pelvis bones which demonstrate that the 3D + O algorithm produces apparently sharper and more continuous surfaces than the other two methods. The 3D + O method also appears to be less sensitive to typical soft tissue interfaces compared to the previous methods. Specifically, the bottom row illustrates that the 3D + O method is able to extract the correct bone surface even when the bone response is weak due to shadowing from muscle and fascia interfaces above the bone surface, which is a common situation when obtaining scans from the pelvis. The other two methods, 3D + E (22) and 2D + O (23) mistakenly identified soft tissue interfaces instead of producing an appropriate bone boundary response (Figure 7).
Quantitative results for phantom study

The fiducial registration error (FRE) for the 25 US volumes averaged 0.31 mm (SD: 0.21 mm) (Figure 8). The mean bone surface localization error (SLE) for 3D + O in the phantom study was 0.28 mm (SD: 0.24 mm) compared with 0.33 mm (SD: 1.31 mm) for 3D + E (22) and 0.33 mm (SD: 0.71 mm) for 2D + O (23).

No statistically significant difference was found between the mean SLEs using the three techniques (one-way ANOVA, $P = 0.9$). However, the standard deviation (SD) of the 3D + O method was significantly lower (F-test comparison with Bonferroni correction, $P < 0.001$) than the others. Furthermore, the surface quality metric was significantly lower with the 3D + O method ($0.4 \text{ mm}^2$) compared with both 3D + E and 2D + O ($2.2$ and $0.7 \text{ mm}^2$, respectively) (22,23) (one-way ANOVA with post-hoc Bonferroni correction, $P < 2\text{e-}8$), which suggests that the 3D + O method is less sensitive than the previous two methods to soft tissue interfaces and typical US imaging artefacts (Figure 9).
Quantitative results for clinical study

For the clinical study, the surface matching error (SME) using the 3D + O method was markedly lower than both other methods at 0.51 mm (SD: 0.43 mm) compared with 1.66 mm (SD: 1.21 mm) for 3D + E (22) and 1.46 mm (SD: 1.04 mm) for 2D + O (23) (one-way ANOVA, \(P < 0.005\) with post-hoc Bonferroni correction). The standard deviation (SD) of the proposed method was likewise significantly lower (F-test with Bonferroni correction, \(P < 0.001\)). The 3D + O method also consistently achieved significantly better surface quality results in the clinical study (~0.13 mm²) compared with the 3D + E (22) and 2D + O (23) methods (0.6 mm² and 0.3 mm², respectively) (one-way ANOVA with post hoc Bonferroni correction, \(P = 0.0017\)).

Discussion

In this study we investigated whether automatically optimized 3D Log-Gabor filters allow the extraction of more accurate bone surfaces from US data, in the context of orthopaedic trauma surgery, compared with our previous local phase-based approaches with empirical parameter tuning (22,23). We proposed a data-driven approach based on the characteristics of bone boundaries in US for selecting 3D Log-Gabor filter parameters on a per-volume basis.

The improvement achieved in terms of surface quality when compared to the previous 3D empirically-set parameter approach was significant: the surface quality metric was reduced by 81% and 77% for phantom and clinical data, respectively, where a value of zero is ideal. The surface localization or surface matching errors were also improved by an average of 15% (not statistically significant (n.s.s.)) and 69% on phantom and clinical data, respectively, when compared with the 3D method with empirically-set parameters (22) (note that since we don’t have a ‘gold standard’ reference surface in the clinical case, these measures are not directly comparable). Furthermore, the proposed approach produced decreases of 81% and 64% in the standard deviations of the surface...
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localization or matching errors (SLE/SME) compared with the previously reported 3D method with empirically set parameters (22) for phantom and clinical data sets, respectively.

We have also compared the 3D + O method to our previously developed 2D parameter optimization method (23). 2D methods (18) ignore the correlations between adjacent slices and are therefore subject to large spatial compounding errors as well as errors associated with the US beam thickness effects. We have shown that extending the automated parameter optimization method to 3D produces significant improvements in the surface quality metric (reduction of 58%) and SME (reduction of 65%) for clinical scans compared to the 2D method (23). For the phantom study, improvements of 43% in the surface quality metric and 15% in the SLE were found, but neither was statistically significant. Again the proposed method decreased the variability (i.e., the standard deviation of the bone SLE/SME) when compared with the previously reported 2D method (23) by 66% and 58% for phantom and clinical data sets, respectively.

Improvement in the SLE for the phantom data when using the 3D + O method was noticeably lower compared with improvement in the SME for the clinical scans; this is likely due to the simpler and more favourable geometry of the bone sample in the phantom setup which may have minimized difficulties with the previous methods. For example, during the collection of the phantom data, we had no difficulties orienting the US transducer in order to get good reflections from the bone surface. When extracting local phase bone surfaces from US scans where a clean bone surface reflection is present (i.e. little soft tissue artefact and where the bone surface is visible as the highest intensity in the whole image), empirical filter parameters were almost as successful as the optimized filter parameters. In contrast, under clinical conditions where the bone surface may not be optimally oriented relative to the US probe and where the properties of the overlying tissues may be more complicated, both previous methods exhibited significant increases in the surface errors – from under 0.5 mm SLE in the phantom setup to roughly 1.5 mm or more SME in the clinical setting – whereas the 3D + O method was relatively unaffected, rising to only 0.5 mm SME in the clinical scans from 0.3 mm in the phantom. Although SLE and SME values are not directly comparable, the SME represents a lower bound for the SLE, so the increases in the clinical setting indicate that the SLEs would have risen by at least this much.

The results presented in this work are comparable to previously reported results for other bone segmentation methods (10,11), where mean errors of 0.3 mm–0.6 mm were reported. However, these studies were done using a 2D US transducer in which the transducer was optimally aligned relative to the bone surface by a trained sonographer to achieve the best surface response. In addition, both methods incorporated bone surface continuity information into their proposed framework. Such an approach will likely fail when the imaged bone surface involves a fractured region and will thus limit the use of these methods to applications in which the bone surfaces are comparatively smooth. In contrast, our proposed method is fully three-dimensional and can deal with relatively arbitrary transducer orientations, which can potentially reduce or eliminate the need to have a trained sonographer operating the equipment; this would make the integration of this imaging modality into the operating room framework considerably easier. Furthermore, though not directly demonstrated in this paper, this processing method is in principle able to handle fractured bone segments and gaps directly, as it does not incorporate pre-operatively-defined models of intact bone.

One limitation of our method is the computational time involved in processing the 3D image volumes. Currently, using algorithms implemented in Matlab on an Intel Core i7 870 CPU @ 2.93 GHz with 8 GB of RAM computer, it takes approximately 47 s to process a single volume. We are currently exploring alternative forms of coding the algorithm. Recently, we have shown that by implementing the 3DPS method on a multi-processor graphic processing unit (GPU) a 15-fold speedup in computation time could be achieved (36). Additional limitations in using US are limitations in the imaging depth and the inability to see beyond the first bone interface. These issues may cause difficulties when imaging intra-articular structures (complex fractures), joint surfaces or deep bone interfaces beneath a thick layer of muscle tissue (such as bone surfaces inside the pelvic ring area). However, most complex distal radius and pelvis ring fracture cases have a pre-operative CT scan performed routinely, so scans obtained from US-accessible regions could potentially be registered to the pre-operative CT data to provide useful intra-operative guidance. In particular, we have recently proposed a near real-time US-CT registration algorithm where local phase bone surfaces were registered to a pre-operative CT scan (37).

Results achieved from quantitative and qualitative experiments imply that Log-Gabor filter parameter optimization is necessary for accurate extraction of bone surfaces from in vivo and in vitro US data. The proposed method holds promise to be useful in orthopaedic surgery procedures where US imaging is employed as an intra-operative imaging modality. More clinical studies are needed to establish the potential value of this new surface extraction method. Our future work will focus on validating the surface extraction and registration approaches on clinical scans that are more representative of specific orthopaedic procedures that we wish to apply our algorithm to (e.g. pelvic ring fractures).

Conflict of Interest

The authors have stated explicitly that there are no conflicts of interest in connection with this article.

Funding

No specific funding.
Appendix

ETHICS CERTIFICATE OF EXPEDITED APPROVAL: RENEWAL

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<tr>
<th>PRINCIPAL INVESTIGATOR:</th>
<th>DEPARTMENT:</th>
<th>UBC CREB NUMBER:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pierre Guy</td>
<td>UBC/Medicine, Faculty of/Orthopaedics</td>
<td>H06-03147</td>
</tr>
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INSTITUTION(S) WHERE RESEARCH WILL BE CARRIED OUT:

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<tr>
<th>Institution</th>
<th>Site</th>
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<tr>
<td>Vancouver Coastal Health (VCHRI/VCHA)</td>
<td>Vancouver General Hospital</td>
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</table>

Other locations where the research will be conducted:

The investigation of the obtained scans (Ultrasound, CT, and X-ray) using state of the art image processing techniques will be done at the Biomedical Signal and Image Computing Laboratory-Department of Electrical and Computer Engineering, UBC campus.

CO-INVESTIGATOR(S):

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Robert N. Rohling

SPONSORING AGENCIES:

N/A

PROJECT TITLE:

Bone Fracture Alignment Assessment Using 3D Ultrasound Imaging – A Pilot Study

EXPIRY DATE OF THIS APPROVAL: August 24, 2013

APPROVAL DATE: August 24, 2012

CERTIFICATION:

In respect of clinical trials:

1. The membership of this Research Ethics Board complies with the membership requirements for Research Ethics Boards defined in Division 5 of the Food and Drug Regulations.
2. The Research Ethics Board carries out its functions in a manner consistent with Good Clinical Practices.
3. This Research Ethics Board has reviewed and approved the clinical trial protocol and informed consent form for the trial which is to be conducted by the qualified investigator named above at the specified clinical trial site. This approval and the views of this Research Ethics Board have been documented in writing.

The Chair of the UBC Clinical Research Ethics Board has reviewed the documentation for the above named project. The research study, as presented in the documentation, was found to be acceptable on ethical grounds for research involving human subjects and was approved for renewal by the UBC Clinical Research Ethics Board.

Approval of the Clinical Research Ethics Board by one of:

Dr. Peter Loewen, Chair
Dr. Stephen Hopkinson Cann, Associate Chair
References