Automated bone contour detection in 3D B-mode ultrasound images using optimized phase symmetry features – a clinical evaluation for pelvic fractures

HACIHALILOGLU I[1], ABUGARBIEH R[1], HODGSON AJ[2], PIERRE G[3]

[1]*Department of Electrical and Computer Engineering, University of British Columbia, Vancouver, BC, Canada*
[2]*Department of Mechanical Engineering, University of British Columbia, Vancouver, BC, Canada*
[3]*Department of Orthopaedics, University of British Columbia, Vancouver, BC, Canada*

ilkerh@ece.ubc.ca

Introduction: Due to its ease of use, portability, low cost, real-time response and absence of ionizing radiation, ultrasound (US) imaging could potentially be an important tool for non-invasive diagnostic imaging in orthopaedics. Unfortunately, the use of ultrasound in orthopaedic surgery is relatively uncommon due to the poor quality of bone surfaces in US images compared to X-ray, computed tomography (CT) or magnetic resonance imaging (MRI). Nonlinear characteristics of ultrasound, low signal-to-noise ratio, speckle, and reverberations make it difficult to accurately and reliably determine the location and shape of the bone surface. Recently, local phase-based image processing methods have been shown to perform very well at locating bone surfaces in ultrasound images, with reported accuracies of better than 0.4mm [1-5]. The local phase features are extracted by filtering the B-mode US image in the frequency domain with a Log-Gabor filter. Although successful results were achieved, accurate localization is highly affected by the choice of filter parameters. The shape, orientation, and scale of the anatomical structures as well as noise in the image must be taken into account during the optimization of the filter parameters. Recently, our group proposed a method of automatically selecting the scale, bandwidth and orientation parameters of Log-Gabor filters in order to optimize the local phase symmetry in US images. Our approach incorporates estimates of principal curvature computed from the Hessian matrix and directional filter banks in a phase scale-space framework [6]. Last year [8], we showed our first clinical results using local phase information to identify fractures from B-mode US images using the method explained in [6]. The objective of the current study was to determine if the proposed automatic parameter selection method could produce accurate pelvic bone surface shapes in a live clinical setting by comparing the surfaces extracted from US images acquired from trauma patients in a hospital with CT scans obtained from these same patients.

Methods: CT scans were obtained as part of normal clinical care from ten patients admitted to Vancouver Hospital (a Level 1 trauma centre) for pelvic fractures. A 'gold standard' bone surface was computed from the CT scan. After obtaining informed consent, we performed an additional US scan using a commercially-available real-time scanner (Voluson 730, GE Healthcare, Waukesha, WI) with a 3D RSP5-12 transducer. The scans were collected from the regions of the iliac crest, iliac fossa and ilium. The phase symmetry (PS) bone surfaces were extracted from the US scans using the empirical Log-Gabor filter parameters [4] and optimized Log-Gabor filter parameters [6]. The bone surfaces on CT were extracted using a standard thresholding approach that minimizes the intra-class variance [7]. The US images were then registered to the CT images using a feature-based rigid registration algorithm with manual landmarking [8]. The quality of the resulting surface matching was evaluated by computing the root mean square distance between the two surface representations [7-8].

Results: Figure 1 (a) shows a 2D slice from a 3D B-mode US image obtained by scanning the patient in the region of the ilium and the corresponding PS images obtained using the Log-Gabor filter with empirical filter parameters (b) and the optimized filter parameters (c). As we have demonstrated earlier, selecting the filter parameters empirically [3] is likely to retain some areas of speckle and some soft tissue interfaces (white arrows in Fig. 1 (b)) in addition to the desired bone surfaces since there is no explicit mechanism for distinguishing between these features. In contrast, the parameter optimization method [6] is able to make a more appropriate selection of filter parameters. The bottom row of Fig.1 shows the B-mode US image (a) and optimized PS image (c) overlaid, after registration, on the corresponding CT slice. The fiducial registration error was 0.31mm (SD 0.25mm). We found the surface fitting error (SFE) between the two surfaces by identifying the location of the peak intensity pixel in each vertical column of the phase-processed 3D US data set and computing the RMS distance to the thresholded surface on the registered CT image. The SFE was 0.72mm (SD 1.24 mm) for PS surfaces extracted using empirical filter parameters and 0.41mm (SD 0.44 mm) using the optimized filter parameters.

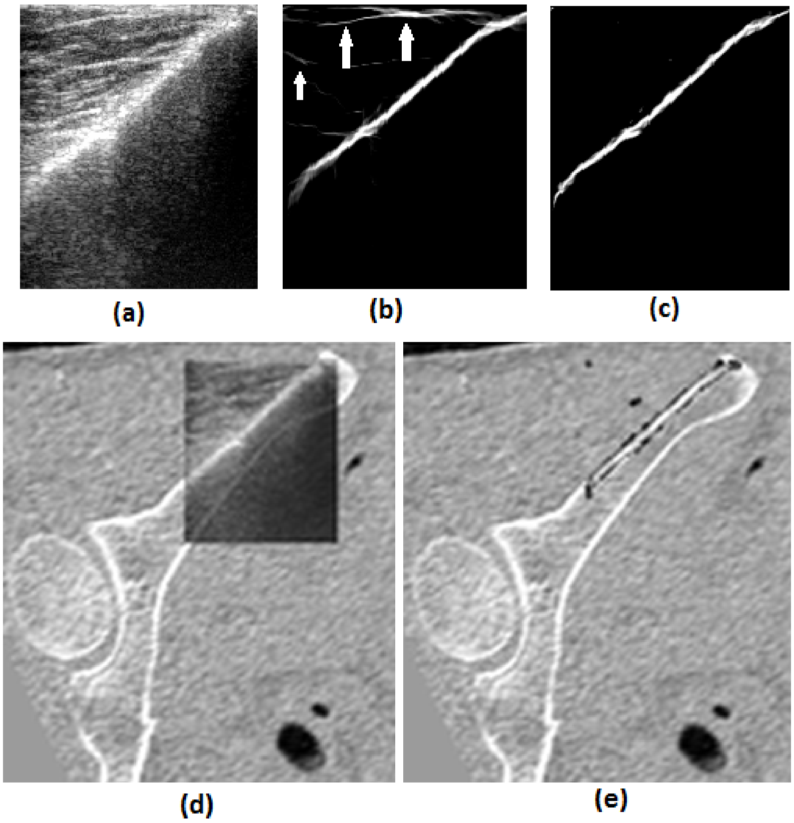

Fig.1. A patients pelvis.(a) B-mode US image obtained by scanning a in vivo human pelvis from the ilium region, (b) Local phase symmetry image obtained using empirical Log-Gabor filter parameters, (c) Local phase symmetry image obtained using optimized Log-Gabor filter parameters and B-mode (d) and optimized phase symmetry (e) US images overlaid on the corresponding CT slice.

Discussion: In this study, we have demonstrated both qualitatively and quantitatively that our automatic filter parameter selection process can be applied successfully to a bone surface extraction task on 3D US images acquired under clinically realistic conditions. The accuracy of the resulting bone surface is excellent, with an average discrepancy relative to a CT standard of well under a millimeter. This level of accuracy is likely to be sufficiently good for a number of important surgical tasks, including CT to US registration, which we are currently working on, and monitoring fracture reduction with less radiation than current practices.

References

1. Mulet-Parada et al. 2D+T boundary detection in echocardiography. Medical Image Analysis. 2000; 4 (1): 21-30.
2. Grau V et al. Adaptive multiscale ultrasound compounding using phase information. Proc MICCAI 2005. Lecture Notes in Computer Science 3749:589-596.
3. Hacihaliloglu I et al. Bone segmentation and fracture detection in ultrasound using 3D local phase features. MICCAI 2008:287-295
4. Hacihaliloglu I et al. Enhancement of bone surface visualization from 3D ultrasound based on local phase information, IEEE International Ultrasonics Symposium 2006:21-24
5. Hacihaliloglu I et al. Bone Surface Localization in Ultrasound Using Image Phase Based Features, Ultrasound in Medicine and Biology, 2009, volume 35, number 9: 1475-1487.
6. Hacihaliloglu I. et al. Automatic Data-Driven Parameterization for Phase-Based Bone Localization in US Using Log-Gabor Filters, International Symposium on Visual Computing, 2009:944-954.

7. Hacihaliloglu I. et al. Assessing Surface Localization Accuracy in 3D Local Phase Ultrasound Images Using CT Reference Images, Computer Assisted Orthopaedic Surgery (CAOS), 2009:137-140.
8. Hacihaliloglu I. et al. Automatically-Optimized Local Phase Features of Ultrasound Images: First Clinical Study, Computer Assisted Orthopaedic Surgery (CAOS), 2010:257-260.