

Registering intra-operative ultrasound with computed tomography using Gaussian mixture models

BROUNSTEIN A¹, HACIHALILOGLU I², GUY P², HODGSON A³, ABUGHARBIEH R¹

¹*Department of Electrical Engineering, University of British Columbia, Vancouver, BC, Canada*

²*Department of Orthopaedics, University of British Columbia, Vancouver, BC, Canada*

³*Department of Mechanical Engineering, University of British Columbia, Vancouver, BC, Canada*

abrou@ece.ubc.ca

Introduction: An important prerequisite of minimally invasive computer assisted orthopaedic surgery (CAOS) is the precise registration of a preoperative plan to the patient's anatomy. Ultrasound (US) has recently emerged as a desirable intra-operative imaging modality for orthopaedic surgery, as it is safe, inexpensive, portable and can provide real-time 3D images. Despite the many advantages, US suffers from a poor signal-to-noise ratio, artifacts and a small field of view, which complicate the registration process. Recently we have proposed a near real-time point-based technique in which US-to-CT registration is achieved using Gaussian Mixture Models [1].

The purpose of this study was to assess the accuracy of our image registration technique on scans obtained from a carefully designed phantom setup and on pelvis scans obtained from trauma patients with pelvic ring fractures.

Methods: When using US for orthopaedic purposes, we have the advantage of strong image responses due to hard tissues. To use these bones surfaces in a point-based registration method, we must first extract this bone information. Bone surfaces appear as ridge-like structures in B-mode US images. We can detect these structures with local phase features using a method called phase symmetry (PS), first used for US by Hacıhaliloğlu et al [2]. PS uses Log-Gabor filter banks to extract local phase information and detect regions where the even phase response outweighs the odd response. These regions are symmetric around an axis determined by the angular component of the Log-Gabor filter. In US images, PS accurately localizes the bone surfaces; however, soft-tissue interfaces are often extracted as well. Hacıhaliloğlu et al. later extended their method to automatically obtain optimized parameters of the Log-Gabor filters to ensure soft-tissue interfaces were not captured [3]. For this study, bone surfaces from US scans were extracted using the optimized Log-Gabor filter parameters [3]. Once the bone surfaces were localized in the US images, ray-tracing was used to select the maximum PS value along the direction of the US probe to extract the final bone surface. A simple thresholding method was used to extract the bone surfaces from the CT volume. The resulting bone surfaces were comprised of approximately 20, 000 pixels. To register the volumes in real-time, these extracted points were further sub-sampled, retaining only 5% of the original surface points. Finally, to ensure registration was anatomically accurate and robust, we reinforced the simplified point cloud with high-curvature features extracted using a Gaussian curvature metric. The registration was accomplished by first modeling the point clouds as 3D Gaussian Mixture Models, which are statistical models that represent population of points as a set of k Gaussian models. The registration was done by iteratively minimizing the L2 distance between the Gaussian Mixture Models [4].

For quantitative validation, we constructed a radio-opaque phantom from a Sawbone (Pacific Research Laboratories, Vashon Washington) male hemi-pelvis and submerged it in a PVC gel with seventy fiducials embedded approximately 1-3 cm away from the bone surface. The phantom was scanned in a Scanco Xtreme CT, model number HRpQCT, which had an isotropic resolution of 0.25mm. A General Electric Voluson 730 Expert Ultrasound Machine was used with an RSP5-12 3D probe. Forty US scans were acquired with a scan dimension of 152x198x148 voxels and isotropic resolution of 0.25mm. For the clinical study, we obtained US scans from eight consenting patients admitted to Vancouver Hospital (Level 1 Trauma Centre) for pelvic fractures clinically requiring a CT scan. 3D US scans were obtained from the iliac crest, iliac fossa and ilium using the same US machine.

Results: We evaluated the surface registration error (SRE) and target registration error (TRE) of the fiducials for the phantom datasets. The SRE was calculated as the root-mean-square Euclidean distance between the registered bone surfaces. The average TRE for the 40 datasets was 2.57mm (SD =1.5 mm). The SRE was 0.35 mm (SD = 0.1 mm). We observed an average runtime of 0.99 seconds for the phantom datasets. The average SRE for the in-vivo datasets was 0.60 mm (SD = 0.34 mm). The average runtime for the registration component of the clinical results was 2.5 seconds. Qualitative results of the clinical validation can be seen in Figure 1.

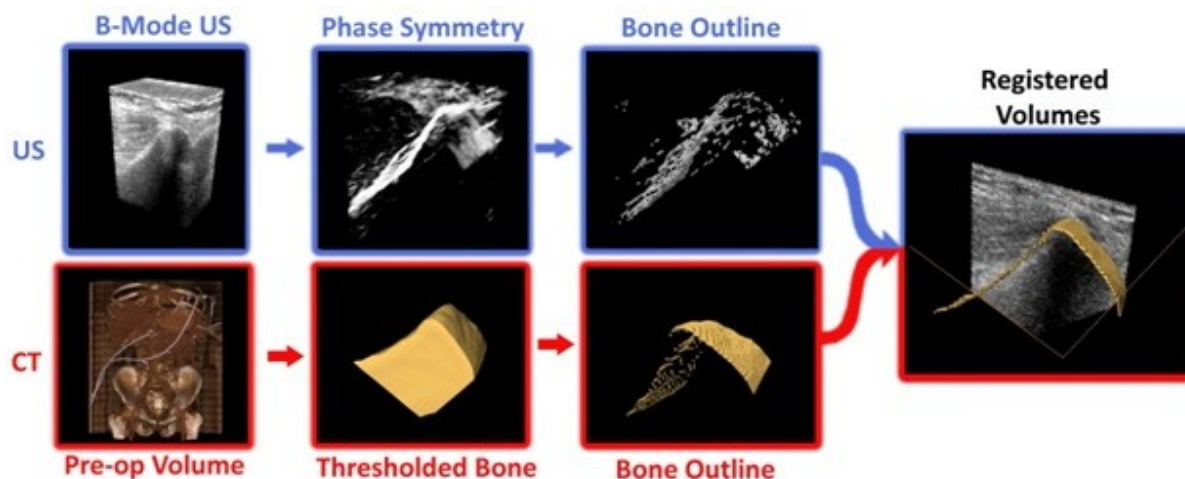


Figure 1. Qualitative results of the in-vivo validation. The PS volume is calculated from the B-Mode US volume acquired intra-operatively from the patient. The CT volume is thresholded and cropped to the region of interest. The bone is segmented from both the PS volume and thresholded CT volume. These outlines are registered using GMM registration.

Discussion: In this study, we have validated our previously developed US-CT registration method on a carefully designed phantom setup and on clinical scans obtained from trauma patients with pelvic ring fractures. To minimize the localization of soft-tissue interfaces in the in-vivo US, we incorporated automatically optimized parameters for phase symmetry. We have demonstrated that we can automatically register 3D US and CT volumes with millimeter-scale errors in 1-3 seconds on both phantom and clinical data. In the future, we plan to implement the PS image processing method component on a graphical processing unit to decrease the runtime and continue our clinical study.

References

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