NEW APPROACHES TO CALIBRATION AND SEGMENTATION IN INTERVENTIONAL ULTRASOUND

Gabor Fichtinger, Emad M. Boctor, and Gregory D. Hager

Engineering Research Center for Computer Integrated Surgical Systems and Technology
The Johns Hopkins University, http://www.cisst.org
{gabor, boctor, hager}@cs.jhu.edu

ABSTRACT

We outline new approaches to ultrasound (US) probe calibration and US image segmentation that we have developed for computationally guided minimally invasive interventions. Computational US guidance generally requires tracking of the ultrasound images relative to a surgical tool such as a needle or tissue ablator. This in turn necessitates a calibration process. We present a calibration method that is accurate, easy to perform, and supports calibration quality control during use. Treatment planning and monitoring often involves segmentation of anatomical details and structures in the US images. We present new model-based methods for segmenting anatomic structures using tissue stiffness properties calculated from displacement and strain images. We present preliminary results of these methods in phantom and ex-vivo animal experiments.

1. INTRODUCTION

During the past several decades, the execution of interventional procedures has been revolutionized by the introduction of advanced imaging methods combined with new computational algorithms for image-based planning and guidance. In particular, ultrasound has emerged as a widely popular image guidance modality, since it is real-time, safe, convenient to use in the operating room, and inexpensive compared to other competing imaging modalities. As a result, significant research has been devoted to 3D real-time visualization of the internal anatomy with US [1].

When using 3D US as a surgical guidance modality, one must track both the imaging probe and surgical tool, typically with some sort of magnetic or optical tracking device. In order to relate structures in ultrasound images to the tool, a fixed transformation between the US beam and a point on the ultrasound head observed by the tracking device must be determined. Obtaining this fixed transformation is referred to as US calibration. Once the US probe is tracked and calibrated, one can sweep the 2D probe and compound the individual images into a volume for use in surgical planning. Consequently, the accuracy of calibration greatly affects the accuracy of surgical planning and execution.

Contemporary calibration methods compute the unknown transformation parameters that maximize the similarity between US images acquired from a phantom and locations predicted by some geometrical description of the phantom [2]. There is error associated with each stage of the calibration process (phantom fabrication, image acquisition, spatial registration, image processing, formulation, and numerical optimization solution), the combined total of which is often significant. But more importantly, pre-procedural calibration depends on the assumption that none of the parameters will actually change during the procedure. This assumption is a priori false and may lead to hazardous situations in the operating room. First, the speed of sound in the phantom and its surrounding medium is different from the speed of sound in the human body. This ultimately leads to depth measurement errors that may reach several millimeters in magnitue and that may be clinically significant. Second, faulty tracker readings or inadvertent changes in the image polarity, scale, or resolution also lead to instantaneous miscalibration between the US image and the surgical tool. These errors are undetectable in the operating room. Furthermore, \pre-operative calibration must be repeated frequently and periodically, which creates a significant expense over time. Hence the only safe, reliable, and inexpensive approach is to perform real-time intra-operative calibration in the background as the patient is being scanned during the procedure.. When calibration is performed repeatedly in this way, any discrepancy or change in the calibration parameters can indicate a hazard situation and the clinician can be alerted about the potential malfunction. Thus calibration can be converted into a safety tool from a technical nuisance and financial burden. In this paper we present the fundamentals of such a a real-time intra-operative calibration and quality control / safety tool.

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Image segmentation is a large and constantly growing area of medical image analysis. Accordingly, a significant body of prior art exists on processing ultrasound data. The family of US segmentation methods has grown so large that we cannot possibly review them in this short paper. What is particularly relevant here is that, while existing methods differ in many aspects, they share one common feature. They all work with US images in "diagnostic" mode, with the purpose of producing complete images of uniform quality over the entire field of view. It is very important to guarantee uniform image quality; otherwise diagnostic veracity may be compromised. Interventional imaging, however, has fundamentally different needs. Interventions are performed according to some treatment plan that is based on pre-operative information and images. When performing the intervention, the physician has a detailed mental model of the process and the anatomy, as well as the location, shape, and size of the target and surrounding tissues. Pre-operative models are often used in the analysis of intra-operative images in model based segmentation scenarios. These models, however, are not used in actually forming and producing the images. In this paper we outline a new paradigm for model-based US image formation, which produces the outlines of the modeled anatomical structures. We exploit the fact that different anatomical structures tend to have different hardness and stiffness. This phenomenon gave rise to the field of elasticity imaging [3]. Here we introduce the concept of model-based elasticity imaging, in order to obtain accurate segmentation of solid structures suspended in background tissues of different stiffness. Our initial investigation pertains to targeting and monitoring thermal ablation of liver cancer, but the method is applicable more generally.

2. IN-VIVO ULTRASOUND CALIBRATION

All conventional phantom-based calibrations depend on non-linear optimization [2], which is a lengthy and computationally intensive process that prevents real-time performance. The key to in-vivo calibration is a closed form mathematical description that allows for real-time evaluation of the calibration matrix [4]. Figure 1 presents the coordinate systems for the closed form formulation: A_1, A_2 are the transformations of US image coordinate system (P) with respect to the reconstruction coordinate system (C) at poses 1 and 2 respectively. From A_1, A_2, we have the transformation between US image coordinate system at pose 1 and 2, $A=A_2A_1^{-1}$. Let us assume for now that we can conveniently estimate A by estimating both A_1 and A_2. Then B_1 and B_2 are the tracking device readings for the sensor frame (R) with respect to tracker reference frame (T) at poses 1 and 2, respectively. Again the relative pose between sensor frame (R) at pose 1 and 2 is given by $B = B_2^{-1}B_1$. This yields the homogeneous matrix equation

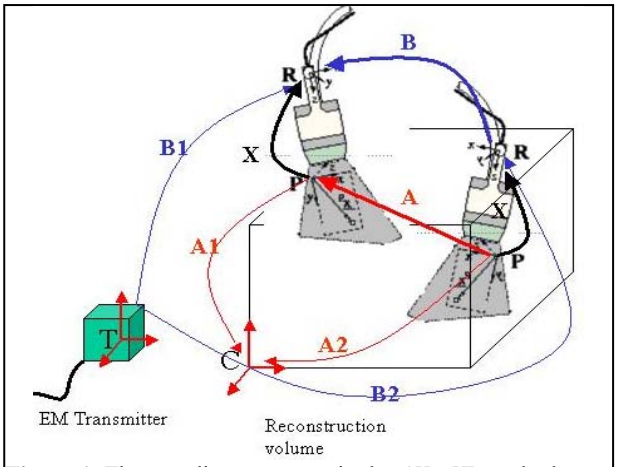

Figure 1: The coordinate systems in the $AX = XB$ method.

$AX = XB$, where A is estimated from images, B is assumed to be known from the external tracking device, and X is the unknown transformation between the US image coordinate system and the sensor frame (R).

The system can be solved in two steps: first extract the rotation, and then solve for the translation and scale [4,5]. Now the remaining missing link is to estimate the A matrix, the motion of the US images between during probe motion. We accomplish this via direct image registration derived from the Sum of Square Differences (SSD) trackers developed for computer vision [6].

The resulting workflow in the real-time in-vivo calibration quality control is described in Figure 2. The *Acquisition*

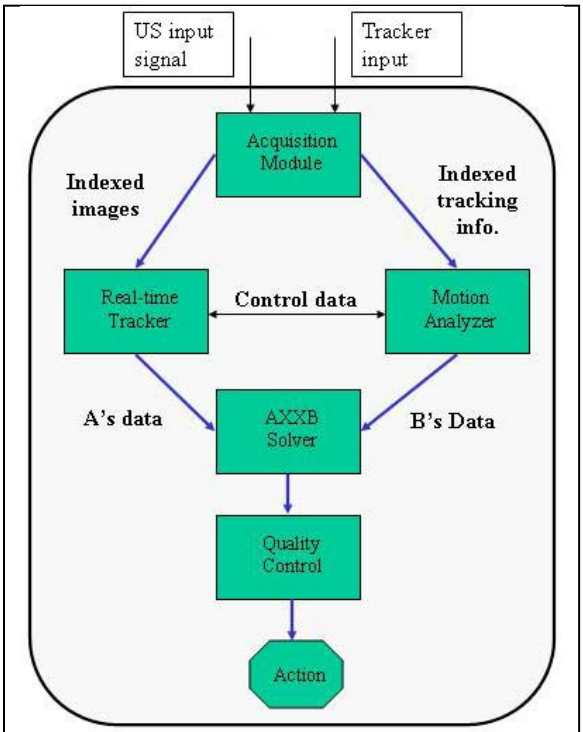

Figure 2: Real-time in-vivo calibration and quality control workflow.

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Module receives the US video signal and tracker readings, from which it prepares synchronized indexed sequences of images and tracking information. The *Motion Analyzer* sorts out the types of motions in these sequences and sends a control signal for the *Real-time Tracker*, which recovers the *A* matrices. As we said earlier, the *AX=XB* system is solved in two steps, first for rotation and for translation. Hence the tracker is used to reject images with translation when the rotation is recovered and then reject images with rotation when translation is recovered. Finally, the *AX=XB* solver receives corresponding *A* and *B* data, and recovers the *X* calibration matrix. The *Quality Control* unit analyzes the new calibration and compares it with previous runs. In case of suspected discrepancy, an appropriate *Action* is initiated to deal with a hazard condition. The action could range from generating a warning message to demanding a halt of the procedure and full recalibration of the system.

For experimental demonstration we collected 5 B-mode datasets from 20 probe motions, with a rectangular view at 8cm depth. One of the datasets contained 4 motions and it was obtained under a faulty condition: we purposely flipped lateral polarity of the B-mode image to simulate a common operator error. The control system picked up the error immediately and reported 180 degree change in the rotation matrix. Further studies [4] showed that the system could recalibrate within 1.5 seconds at normal scanning was robust to speed and normal probe motions.

3. ELASTICITY BASED SEGMENTATION

Our model-based elasticity segmentation method was described earlier in [7]; here we provide a brief outline. The workflow (in Figure 3) begins with the usual steps of elasticity imaging: we compress the tissue with pressing the probe and introduce about 1-2% strain in the tissue; we collect US data in FR-mode; we calculate a correlation image between uncompressed and compressed images; and we calculate a displacement image for the redistribution of scatterers. Conventional elasticity imaging would continue with differentiating the displacement image and deriving a global strain image. Differentiation, however, amplifies the effects of decorrelation, so the strain image rapidly deteriorates, especially in areas of low correlation. Instead, we utilize prior knowledge about the intervention. In the simplest case, such as demonstrated in Figure 3, we try to locate a stiff ellipsoidal lesion (such as liver cancer) suspended in a more elastic medium (such as healthy liver tissue). The simple elasticity map is captured in a linear finite element model, or FEM. The linear model is quite appropriate because at low strain the strain-stress relationship is linear [7]. We proceed with compressing the FEM model by applying boundary conditions from the true displacement image and we create a so called model displacement. The model displacement does not resemble the true displacement image, because the FEM model was just a

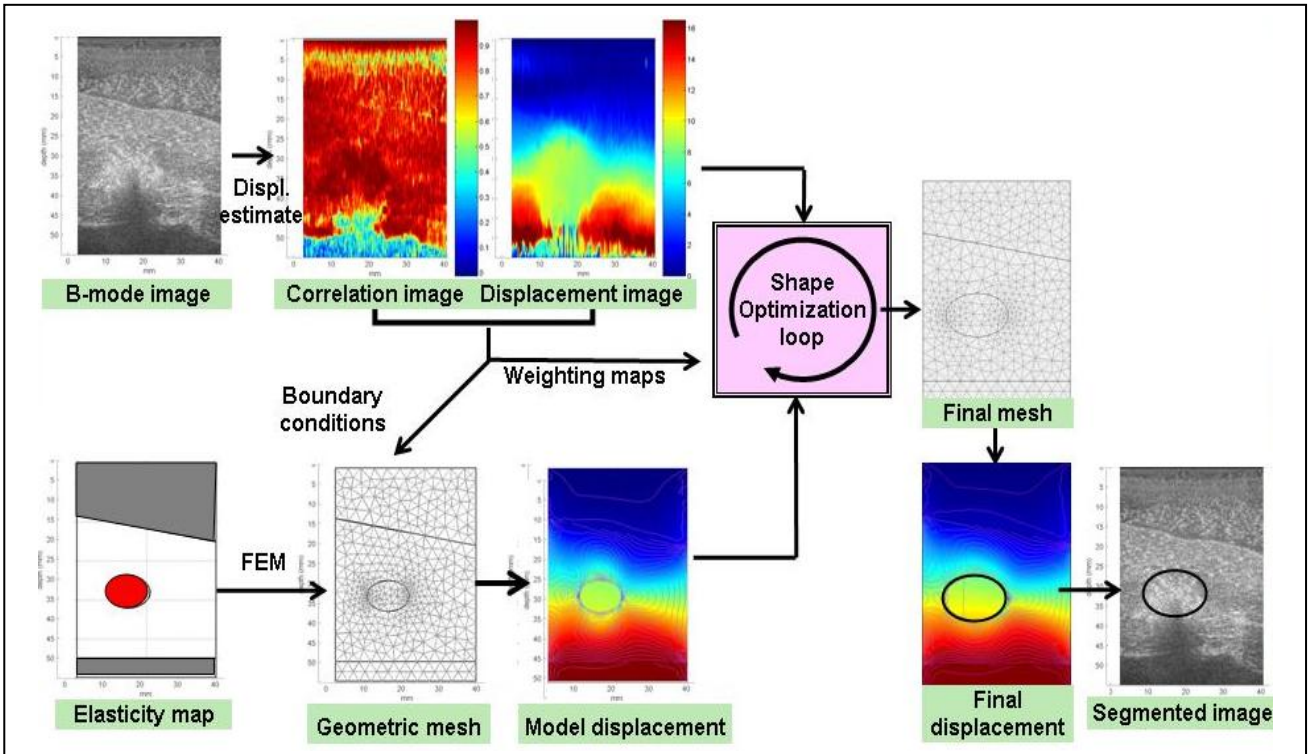

Figure 3: Elasticity based segmentation workflow

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crude guess of reality. Now, we adjust the ellipsoidal lesion model in a shape optimization cycle until the FEM model displacement starts to converge to reality. To improve on the optimization, we use the correlation image for weighting and we modify the FEM model only in the areas where correlation is high, i.e. where we can trust our measurements. At the same time, information flows through the FEM model to areas where we have lower correlation. We stop at the final displacement that is now quite similar to the true displacement. When the shape optimization stops, the final ellipsoid in the FEM model yields the segmented contour of the lesion.

According to Figure 4, the method is remarkably robust to prior estimates of the Young's moduli of the surrounding

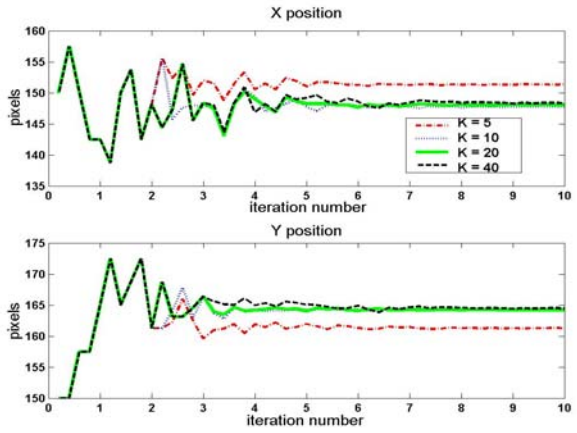

Figure 4: Location convergence of the ellipse. K is the ratio of Young's moduli between ablated lesion and normal liver.

tissue and the lesion. In a liver ablation monitoring study [7], the algorithm converges robustly for a range of Young's moduli between 5 and 40, with 20 being the correct value according to the literature.

A more realistic experimental case is shown in Figure 5, where a thermal coagulation lesion in liver is modeled

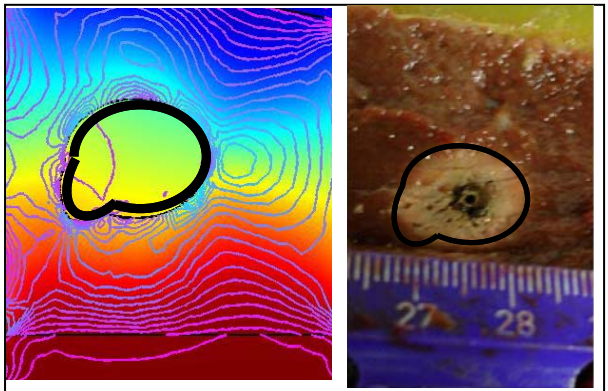

Figure 5: Segmentation of an irregular thermal ablation lesion in liver. Left: final displacement image with final contour; Right: contour superimposed on pathology image.

with two overlapping ellipses. The final contour correlates well with the actual pathology. Generally, a great advantage of the shape model is that the search space in the shape optimization does not grow drastically with adding more details to the model. For example, with adding just one degree of freedom to the 2D ellipse, the model becomes three dimensional with little additional computational cost.

4. CONCLUSIONS

We have presented new approaches to in-vivo self calibration and model based elasticity segmentation. We believe these methods have great promise in improving the clinical utility and safety of interventional ultrasound imaging. At the same time, significant work must still be done to make these methods suitable for clinical utilization. Our ongoing work is devoted to the further development and validation of these algorithms in more extensive and realistic circumstances. We believe these results clearly point to a re-thinking of ultrasound imaging for interventional applications.

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