Automated 3D Freehand Ultrasound Calibration with Real-Time Accuracy Control

Thomas Kuiran Chen¹, Purang Abolmaesumi^{1,2}, Adrian D. Thurston¹, and Randy E. Ellis^{1,3}

School of Computing, Queen's University, Kingston, ON, Canada
Dept. of Electrical and Computer Eng., Queen's University, Kingston, ON, Canada
Dept. of Radiology, Brigham and Women's Hospital, Boston, MA, USA
purang@cs.queensu.ca

Abstract. 3D ultrasound (US) is an emerging new imaging technology that appeals to more and more applications in intraoperative guidance of computer-assisted surgery. In a freehand US imaging system, US probe calibration is typically required to construct a 3D image of the patient's anatomy from a set of 2D US images. Most of the current calibration techniques concern primarily with the precision and accuracy. However, for computer-assisted surgeries that may require a calibration task inside the operating room (OR), many other important aspects have to be considered besides accuracy. In this paper, we propose a novel system for automated calibration that is optimized for the OR usage with real-time feedback and control of the calibration accuracy. We have also designed a novel N-wire phantom, with greatly reduced complexity to facilitate mass production without compromising the accuracy and robustness.

1 Introduction

3D US imaging has seen increasing applications in intraoperative guidance of computer-assisted surgery. Compared to other imaging modalities (e.g., fluoroscopy, computed tomography (CT) or magnetic resonance (MR)), medical US is non-ionizing, compact and portable, relatively inexpensive, and capable of imaging in real time. To construct a high-resolution 3D US image of the patient's anatomy from a set of 2D images, a tracked 2D US probe that allows image acquisition in an unconstrained (freehand) motion is commonly used. Tracking is typically achieved by rigidly affixing the probe with a localizer traced by a position sensing system. However, knowing the position of the US probe alone is not adequate to determine the positions of the acquired 2D images. The relationship between these two coordinate frames can be calculated through a process known as US probe calibration by estimating a homogeneous transformation that maps the position of individual pixels from the US image frame to the US probe frame. The process is usually performed by imaging an artificial object with known geometries, referred to as a phantom. Calibration is therefore a fundamental step an a single point of failure in a freehand US system. A recent and comprehensive overview of the US calibration techniques could be found in [1].

Most of the current state-of-the-art calibration techniques focus primarily on precision and accuracy, which is well justified if the procedure is conducted in a laboratory setup; however, for computer-assisted surgeries that may require calibration inside the OR, many other important aspects have to be considered.

First, sterilization of the US probe needs to remove the spatial localizer. A re-calibration is therefore required in the OR, where a robust and fully automated procedure is always preferred. Overall, there exist two major types of calibration techniques: an iterative approach (e.g., wall, cross-wire and three-wire phantoms) vs. a closed-form solution (e.g., N-wire or Z-fiducial phantoms and the most recent, the Sandwich phantom [2]). Iterative approaches in general are less robust and less efficient than closed-formed solutions [1] and suffer from the non-guaranteed convergence, local minima and sensitivity to initial estimates. In addition, iterative methods typically need more images than closed-form solutions. For instance, the Cambridge phantom [3] (in the wall phantom group) requires capture of at least 550 images. In contrast, inspired by the work in [4], we have previously developed a custom-built N-wire phantom [5] to calculate the calibration parameters in a closed-form solution with less than 30 images and with sub-millimeter accuracy. Most recently, Boctor et al. [2] proposed a closedform calibration method using a Sandwich phantom that requires as few as only three poses of US images. However, due to the generally poor visibility and the abundance of speckles in the US image, automated extraction of the wire points is always challenging for these landmark-based calibration techniques. For example, the current designs of the N-wire phantoms [4, 5, 6] typically require manual segmentation of the US images that is undesirable in the OR. Here we propose a robust and fully automated segmentation method to address this problem.

Another essential element that a conventional calibration system typically lacks for OR is the real-time feedback and control of accuracy. Calibration and validation are commonly two-phase tasks and remain isolated to each other in conventional techniques: first, a calibration is performed followed by a validation; hence, the only way for the surgeons to possibly improve an inaccurate calibration outcome reported by the validation procedure is to recalibrate, which is not only time-consuming but also, more critically, lacking assurance to warrant a satisfactory result in a repeated procedure. Boctor et al. [2] was among the first to address this issue in a *Bootstrapping* method where a closed-form calibration algorithm and a real-time validation procedure were close-looped to iteratively minimize the standard deviation of a 3D reconstruction error by reducing the errors and noise in the pre-collected US images. Reprocessing the pre-acquired data certainly has the advantage of limiting the number of input images to a minimum; on the other hand, depending on how much the image is retouched, it may also result in a final calibration matrix that is overfitting (or biased toward) the specific data collected for that particular calibration. In addition, since a small standard deviation of the 3D reconstruction error does not necessarily guarantee a satisfactory target registration error (TRE), using the error deviation to control calibration accuracy may not be sufficient enough. Inspired by their work, we propose an alternative real-time calibration-accuracy-control mechanism by iteratively minimizing the TRE directly while acquiring new US images for each iteration. This novel approach proves to bring a good balance between the number of input images and the calibration accuracy.

Furthermore, one of the major concerns in the OR is to sterilize the calibration phantom. Most of the current phantom designs are in general complicated and not optimized for such procedure. For instance, existing N-wire phantoms employ a large number of N-fiducials [4,5]. To secure the wires, many holes are drilled on the phantom walls which provide potential hiding place for bacteria.

Finally, individual research groups undergo their custom designs of calibration phantoms that typically do not take costs into consideration. Manufacturing these phantoms for large-scale OR usage is not cost-effective and practical.

To the best of our knowledge, no current calibration system in the literature has ever attempted to address all these concerns and to provide a practical solution that is optimized to be used in the OR. In search for such a solution, we propose a complete system for automated freehand US calibration in the OR with real-time feedback and control of accuracy. We have also designed a novel N-wire phantom (*Kingston* phantom [7]) of greatly reduced complexity without compromising calibration accuracy and robustness. The phantom is cost-effective to make, with great potential for mass production and large-scale OR usage.

2 Methodology

Figure 1 gives a high-level system overview of our proposed US calibration solution. Besides Kingston phantom, the US calibration system consists of four essential components in an iterative closed-loop: US image acquisition and tracking, automated segmentation, closed-form calibration, and real-time accuracy validation. Serving as inputs, US images are continuously acquired from Kingston phantom and tracked in real time by a camera system. The positions of the N-fiducials in the US images are then extracted on-the-fly by an automated segmentation algorithm and together with their corresponding positions in the phantom space, they are fed into a least-squares-based closed-form calibration algorithm that we have previously developed [5] to calculate the calibration parameters. The calibration accuracy is then examined by the validation component in terms of TRE and fed back to the control loop to determine whether the new input data is acceptable and if the current calibration accuracy has reached a satisfactory level. When the TRE starts to converge after a certain number of input images and falls below a desired threshold, the system would terminate its iterations and output the final calibration result.

2.1 The Kingston Phantom

Kingston phantom [7] (Figure 2) consists of only a front and a back plate plus two side walls to form a simple cubic pipe. For effective sterilization, the phantom could be quickly disassembled and reassembled using an L-key screwdriver. To facilitate easy manufacturing, ensure rigidity and durability, and reduce distortion in the phantom geometry during the reassembling, the plates are in plain rectangle-shape and made of stainless steel at 5mm thickness. The front plate has an extended arm to mount a spatial localizer.

We have found, through experiments, that the speckles in US images which challenge automated segmentation are largely contributed by the destructive and

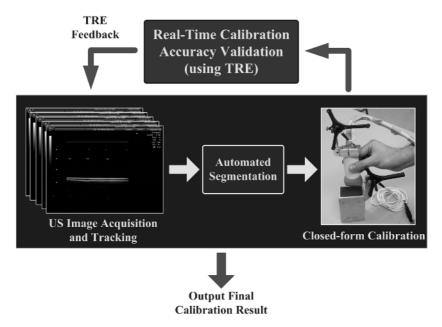


Fig. 1. The design of the proposed US calibration system

constructive interference of US signals traveling through too many N-fiducials arranged typically in parallel. We also discovered that the diameter of the nylon wire has non-negligible influence on the appearance of N-fiducials and at 0.35mm, it gives the smallest while the best defined dots in the image for the US probes we use. As a result (Figure 3), with the selected nylon wire, by reducing the number of N-fiducials to only two in double layers and shifting their positions apart, Kingston phantom produces considerably clean (less speckles) and very well defined images of N-fiducials that may facilitate the automated segmentation.

2.2 Robust and Fully Automated Segmentation

We have developed a fast, robust and fully automated segmentation algorithm to effectively extract the N-wire points in the US images acquired from Kingston phantom. The segmentation algorithm is specifically designed for Kingston phantom, however, the underlying principles could be easily generalized for all N-wire phantoms. The basic idea is to utilize the specific geometric appearance of the N-wires in the image, namely, the unique three collinear dots that form a typical N-wire intersection with the US image plane, and the two almost perfectly parallel lines that pass through these two layers of collinear dots. In general, the automated segmentation is composed of five major stages and employs various image processing techniques:

- 1. Grey-scale morphological operations are first used to remove large noisy parts, while retaining smaller objects in the image;
- 2. A second morphological pass is then employed to remove objects that are too small to represent true N-wire points;

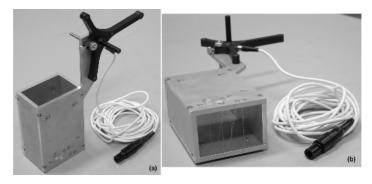


Fig. 2. Front (a) and side (b) view of Kingston phantom

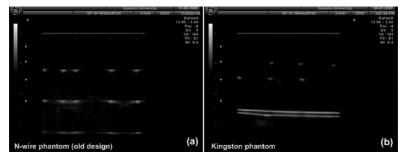


Fig. 3. US images of current N-wire phantom (a) and Kingston phantom (b)

- 3. The remaining pixels in the image are clustered into small regional spots with their centers representing a potential dot;
- 4. A line-search algorithm isolates all possible sets of three collinear dots from the others in the image;
- 5. Finally, a parallel-line-search algorithm locates the pair of parallel lines that are most likely represented by the N-wire points we are looking for.

To test the robustness of the segmentation algorithm to noise, 100 US images were acquired from *Kingston* phantom and we deliberately adjusted the settings of the US machine such that large areas of speckles were presented in the resulting images. The technique has proved itself to be very robust and accurate by correctly locating the true N-wire points in all 100 testing images. Figure 4 shows the segmentation results on one image that has worse-than-average visibility.

2.3 Real-Time Feedback and Control of Calibration Accuracy

Direct evaluation on calibration accuracy is challenging due to the lack of a reliable method to measure the exact spatial relationship of the US image frame to the probe frame. A common walk-around is to measure how close a 3D reconstructed position from the US image is (after applied the calibration parameters) to its actual position, frequently referred to as a Target Registration Error (TRE). Typically, stylus-probe measurement of the 3D position is treated as a

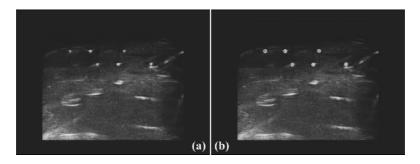


Fig. 4. Robust and automated segmentation results (b) of the original image (a)

golden standard and compared against the US measurement. However, it is impractical to obtain a TRE value for each calibration iteration using such manual procedures. Validation needs to be done automatically and in real time.

The uniqueness of a N-wire phantom is in its special geometry that allows us to identify some key physical features of the phantom both in the phantom space and on the US images, which essentially enables us to solve the calibration matrix in a single closed-form solution using least squares [5, 6]. The same principle could be used to automatically estimate the TRE for each iteration as in Eq (1):

$$\overline{TRE} = X_H - {}_T^H T \cdot {}_P^T T \cdot {}_U^P T \cdot X_U \tag{1}$$

where $_U^PT$ is the current calibration result to be validated, $_T^HT$ and $_T^TT$ are known by the spatial localizer affixed on Kingston phantom and the US probe, and X_H and X_U , the identified positions in the respective phantom and US image space. To avoid systematic errors, X_H and X_U are acquired separately for validation purposes only and should not be used as inputs to the calibration component.

3 Results

US images are generated by a General Electric (GE) Voluson 730 Expert US machine (Figure 5(a)). A Traxtal (Bellaire, TX) VersaTrax Active Tracker is mounted on a 2D linear array US probe (Figure 5(c)) and tracked by a Northern Digital (Waterloo, Ontario) Polaris Optical Tracking System (Figure 5(b)).

A total of 102 US images were acquired from *Kingston* phantom, then randomly selected as inputs to the calibration system. The number of input images ranged from a minimum of 4 to 102 (in which case all images were used). For every number of inputs, 100 independent calibration trials were conducted with images selected randomly per trial, and validated to obtain the TRE distribution. Figure 6 demonstrates the complete TRE distribution and convergence (for all 100 trials) with respect to the number of randomly selected input images along x-axis (the US signal propagating path), y-axis (inside the US image plane), and z-axis (along the US beam thickness direction).

The TREs are converged to 0.32mm, 0.13mm and 1.33mm in x, y and z axis, respectively, which is comparable to that of our old N-wire phantom [5]. The

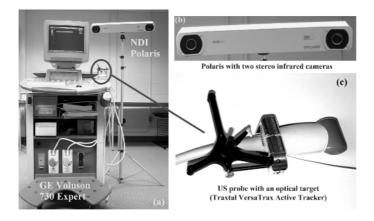


Fig. 5. Experimental setups

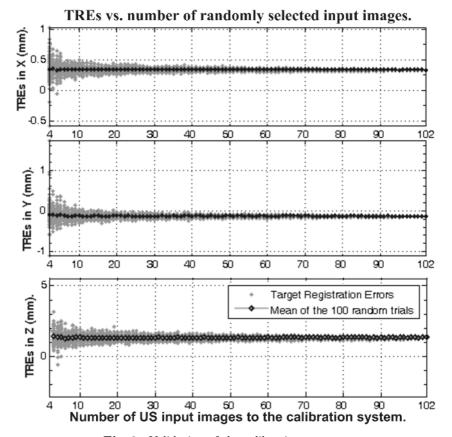


Fig. 6. Validation of the calibration accuracy

central black dots are the means of TREs for the 100 random trials at any given number of input images, which are essentially equivalent to the true converged TRE value. The gray dots are the actual TREs for each random trial and their outer band effectively outlines the converging patterns of TREs along each axis. As we can observe, the TREs start to converge quickly in both x and y directions to below 0.5mm only after 10 input images, and in z direction after 30 images to below 1.5mm. These results are as expected because z-axis is along the US beam thickness direction that has the most uncertainty among all three axes, therefore in general, it requires more images for the TREs to converge.

4 Discussion and Conclusion

We have presented a novel system for automated 3D freehand US calibration that is optimized for the OR usage with real-time feedback and control of calibration accuracy. The proposed system consists of:

- a novel Kingston phantom with greatly reduced complexity to assist OR usage without compromising the calibration accuracy,
- a robust and fully automated segmentation algorithm to extract wire points in the US images of the calibration phantom, and
- a real-time calibration-accuracy-control mechanism to iteratively minimize the TRE directly while acquiring new US image data at each iteration.

Our preliminary results have shown the system has a superior accuracy assurance balanced with real-time efficiency. The design of *Kingston* phantom is also cost-effective with the potential for mass production and large-scale OR usage.

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