Automatic Registration of Pre- and Intraoperative Data for Long Bones in Minimally Invasive Surgery

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Abstract— The Minimally Invasive Procedures (MIP) in orthopedics have grown rapidly worldwide, as clinical results indicate that patients who undergo MIP typically experience minimized blood loss, smaller incision and shorter hospital stays. For most MIP, a preoperative 3D model of the patient anatomy is usually generated in order to plan the surgery. The challenge in MIP consists in finding the correspondence between the preoperative model and the actual position of the patient in the operating room, also known as image-to-patient registration. This paper proposes a real-time solution based on ultrasound (US) images: the patient anatomy is scanned by an US probe. Then, the segmentation and the extraction of bone contours from US images result in a 3D point cloud. The Poisson surface reconstruction method provides a 3D surface from 2D US data which will be registered with the preoperative model (CT volume) using the principal axes of inertia and the Iterative Closest Point robust (ICPr) algorithm. We present quantitative and qualitative results on both phantom and clinical data and show a mean registration accuracy of 0.66 mm for clinical radius scan. The promising registration results show the possible use of the proposed registration algorithm in clinical procedures.

I. INTRODUCTION

O VER the last twenty years, image-guided surgery (IGS) have been greatly expanded by the advances in medical imaging in a range of surgical disciplines including orthope-VER the last twenty years, image-guided surgery (IGS) have been greatly expanded by the advances in medical dic surgery. The IGS permits the surgeon to visualize both the surgical instruments and the patient anatomy together in the same screen with theirs real positions in the operating room. The challenge is to find the correspondence between the patient anatomy in the operating room and the 3D reconstruction model; in other words, the determination of the image-to-patient registration transform. As the patient anatomy considered in this study (long bones) does not change before and within the intervention, only a rigid transformation is considered. Ultrasound (US) is a favorite imaging modality for minimal invasive surgery, as it is inexpensive, safe and real-time. So, several methods to compute the registration between intra-operative US data and preoperative CT data have been proposed in recent years. The most widely used registration method in computer assisted orthopedic systems (CAOS) is the iterative closest point

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algorithm (ICP). Methods have been proposed toimprove the robustness and accuracy of standard ICP [1] because it is quite sensitive to the initial alignment and it easily becomes trapped in local minima.

Moghari et al. [2] proposed a rigid body, point-based registration, based on the Unscented Kalman Filter algorithm. The proposed algorithm is tested and compared with the ICP registration algorithm where the collection of the US data was performed manually. Penny et al. [3] proposed to convert US and CT images into probability maps and then register them. The normalized crosscorrelation is used as a similarity measure to register these images. The Root Mean Square (RMS) of the Target Registration Error (TRE) has an average of 1.7 mm. However the segmentation of both US and CT data is performed manually to create training sets for the probability images. Wein et al. [4] proposed a novel approach for simulation of US images from CT data as well as a new similarity metric to develop a fully automatic imagebased algorithm. However the average RMS TRE obtained with this method was relatively high, 8.1 mm. Yan et al. [5] modified their first proposed method which requires a 3D reconstruction of the 2D US slices of vertebrae. The technique became a slice to volume strategy without the need of a reconstruction in order to make the total registration time more practical intraoperatively. The time was reduced from 8 min to 4 min and the medians of the final TRE was of 0.65 mm for sawbones phantom and of 1.48 mm for porcine cadavers.

In this paper, we propose an automatic real-time registration of 2D ultraound data for minimally invasive computer assisted long bone surgery. The ultrasound transducer is calibrated using a fully automatic method [6] developed in our laboratory for mini-invasive suregery purpose. The calibration has an average point reconstruction error of 0.33 mm. After the calibration step, the patient anatomy is scanned with US probe and the acquired images are segmented in real-time (Fig.1) by a method developed in [7] in order to extract the desired bone surface contour. The use of an optical localizer system together with trackers and a US probe precalibration step make it possible to assign a world coordinate position to any pixel on the 2D US image. The next section deals with the Poisson surface reconstruction, the pre-registration step using the inertia axis and the Iterative Closest Point robust (ICPr) algorithm. The results and discussion will be presented in section 3 followed by the conclusion and the future work.

Fig. 1: Real time ultrasound image segmentation of radius

II. MATERIAL AND METHODS

A. 3D US Data Poisson Surface Reconstruction

The calibration of the 2D US probe permits to find the spatial transformation between the US image pixels and the tracking body attached to the US probe. Based on the calibration, the real-time segmentation of US images provides a 3D point cloud.

When trying to reconstruct the patient anatomy, the speed of scanning turns out to be an issue. On one hand, a relatively fast movement during the acquisition may provide discontinuous 3D contours containing holes. On the other hand, a relatively slow acquisition may lead to overlapping contours. As a result of that, a registration carried out on a raw US point cloud without any improvement operations is a challeging task. We suggest a reconstruction step of the point cloud using the Poisson surface reconstruction algorithm [8] which is not highly sensitive to noise, varying point-density and holes. In fact, the method performs a new resampling of the initial point cloud with a uniform point distribution. This is done with respecting the initial form of the point cloud. The reconstruction works as following: Based on a point cloud and their normals, the algorithm approaches the problem of surface reconstruction using an implicit function framework. It computes a 3D indicator function (defined as 1 for points inside the model, and 0 for the points outside), and obtains the reconstructed surface by extracting an appropriate iso-surface. To prove that the use of Poisson surface reconstruction method is more advantageous than using the US point cloud directly, we compare the registration results obtained in the two cases. In Fig 2, we illustrate the robustness of the Poisson reconstruction method to the presence of holes in the initial US point cloud and the reconstruction of a uniform surface.

B. Automatic Initial Alignment

The ICPr algorithm depends on the initial alignment of the data to be registered. In order to perform an accurate registration, we propose a rough prealignment step of the data. The proposed method consists in matching the centroids and the principal axes of inertia of 3D surfaces. This strategy, which permits to superimpose 3D surfaces by aligning axes and centroids, is based largely on a robust estimate of the 3D object physical characteristics such as volume, center of

mass and the inertia principal axes of the object. We refer to [9] for a detailed presentation of these parameters.

C. ICPr Algorithm

After the step of aligning the 3D US surface reconstructed from the point cloud with the 3D preoperative model, we use the ICPr algorithm [9], a variant of ICP for the registration. The main drawback of the ICP is its lack of robustness and local minima in case of presence of outliers or missing data on the surfaces to be registered. Indeed, in the ICP, all matching points participate equally in the estimation of the transformation. Therefore, the quality of the calculated transformation strongly depends on the quality of the original data. To give less importance to outliers, a commonly used strategy is to introduce a weighting parameter related to the quality of the match [9]. As a result, the registration becomes robust by computing the nearest neighbor of each point of the moving object, and only keeping the supposed good matches. A selection of the Euclidean distance between matched points is performed to select only reliable matches. This process is based on Tukey estimator [9].

D. Gold Standard and Registration Evaluation

The Gold Standard registration transformations between the 3D preoperative model and the intraoperative data were obtained by matching the CT marker points to phantomattached fiducials (Fig. 3) picked by a digitizer.

Let $F^{PREDP} = \{f_1^{PREDP}, f_2^{PREDP}, ..., f_N^{PREDP}\}$ and $F^{INTRAOP} = \{f_1^{INTRAOP}, f_2^{INTRAOP},..., f_{N_{T_{2}}}^{INTRAOP}\}$ be two sets of N correlated fiducials. f_i^{PREOP} and $f_i^{INTRAOP}$ are the correlated fiducial location coordinate vectors in the preoperative and and intraoperative datasets, respectively.

The quality of the registration algorithm is evaluated by calculating the surface registration error (SRE), the fiducial registration error (FRE) and the target registration error (TRE). The SRE was computed as RMS distance error between the two imaging modalities surfaces, the FRE as

Fig. 2: Surface reconstruction of segmented contours from US images : a) Initial US point cloud with holes. b) US Poisson reconstruction

defined in (1) is the RMS distance error between homologous fiducials after registration.

$$
FRE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (T_{US}(f_i^{INTRAOP}) - f_i^{PREOP})^2}
$$
 (1)

where the subscript 'US' denotes transformation computed using US-based registration. The TRE as defined in (2) is the distance error between corresponding points other than the fiducial points after registration.

$$
TRE(p) = || [(T_{US}).(T_{GOLD}^{-1}). p] - p ||
$$
 (2)

where p is the position vector of the bone preopeartive surface voxel (with respect to the preoperative coordinate system) and the subscript 'GOLD' denotes transformation computed using Gold Standard registration. For each phantom registration, the RMS TRE was calculated over all bone surface voxels as an overall measure of registration accuracy.

E. Experimental Setup and Data Acquisition

The fusion of preoperative CT images with intra-operative US images is performed through an NDI Spectra Polaris system and an US transducer (L12-5L60N, Telemed, Lithuania) working in B-mode at frequencies ranging from 5 Mhz to 10 MHz, depths ranging from 30 mm to 120 mm and a field of view of 59 degree/mm.

1) Phantom Study: A phantom sawbone of femur is used to evaluate the registration error of the proposed algorithm. The intraoperative point cloud was collected with the US probe by placing the phantom in a water bath (Fig. 3). Twenty-six 1-mm metal fiducials were attached to the phantom. The registration algorithm was performed 5 times on the same sawbone. The Gold Standard surface was provided by a CT machine (Siemens Biograph). The CT imaging resolution was 0.23 mm x 0.23 mm x 0.7 mm. A thresholding segmentation was performed. A 3D surface mesh was extracted from the segmented CT volume. The mesh was then smoothed and remeshed, leaving an isotropic placed vertex count at N=5500. The fiducials were not considered for registration and were only used for validation purpose.

2) Clinical Study: For the clinical validation, we obtained both CT and US scans of the radius from three human subjects. The voxel resolution for the CT volumes was 0.58 mm x 0.58 mm x 1 mm. The segmentation, smoothing and remeshing processes are similiar to those of the phantom study. We also provide registration accuracy results by computing the SRE.

III. RESULTS AND DISCUSSION

The number of points of the US surafaces representing a half of femur (phantom) is about 4000. The results of the phantom setup showed an average of 2.15mm (SD=0.14 mm) using the Poisson surface reconstruction. Without using this approach the mean SRE increases to 2.55mm (SD=0.14 mm). Another registration comparison results between using

Fig. 3: Phantom validation experiment. (a) Femur phantom with attached fiducials in a water bath. (b) CT-based phantom reconstruction (white arrow pointing to one of the used fiducial)

Poisson surface reconstruction and without is given in Table I. The registration results are better when using the Poisson method and especially when the quality of the initial US point cloud is poor thanks to its capability of filling the holes as well as to its less sensitivity to the noise.

TABLE I: Evaluation of ultrasound-based phantom registration with and without using Poisson surface reconstruction

	Without reconstruction		Poisson Reconstruction	
	FRE	TRE	FRE	TRE
Mean (mm)	1.94	1.78	1.15	0.96
Std. Dev (mm)	0.67	0.50	0.96	0.60
Max (mm)	3.01	4.96	3.25	5.55

TABLE II: Translation and Rotation Registration Error using Poisson Surface Reconstruction

Qualitative results of the registration performed on the femur phantom (from Fig. 4a to Fig .4d) and clinical radius scan (Fig. 4e) can be seen in Fig 4. Fig. 4a and Fig. 4b show the prealignment and ICPr algorithm of the US green surface, respectively. The red fiducials, which have been picked intraopertaively by a digitizer, are close to the preoperative segmented fiducials (in blue) after the ICPr (Fig. 4b). In Fig. 4c, we present the distance map between US and CT surfaces in the last iteration of ICPr. In order to demonstrate the performance of the ICPr algorithm against outliers and missing target data, Fig. 4d depicts the weights (between 0 and 1) corresponding to the contribution of each point of the US surface in the estimation of the registration

Fig. 4: Qualitative registration results on femur phantom and clinical radius scan. (a) Prealignment step: The US surface (before alignment) is presented in red with yellow fiducial spheres, the CT surface is presented in yellow with blue fiducial spheres and the US surface with fiducial spheres after alignment are colored in green and red respectively. (b) ICPr algorithm result. (c) Distance map between the CT model and the US surface after the registration. (d) Color map corresponding to weight value points at the last iteration of ICPr algorithm. (e) Distance map between the CT model and the US surface after the registration for radius scan

matrix at the last iteration. The red points set are neglected due to a lack of information in the 3D preoperative model since we consider just a half CT surface of the phantom.

The average error of translation and rotation after the prealignment and before the ICPr as well as after the ICPr are computed with respect to the Gold Standard transformation as shown in Table II. When exploring the registration results, we can see that the ICPr is robust even in case of a poor prealignement quality. The average run times for the whole registration process (normal estimation, surface reconstruction, prealignment and ICPr) for the phantom study was 3.17 s (SD=0.38 s). The time decreased to 1.06 s (SD=0.44 s) when the US point cloud was used without reconstruction.

For the clinical validation, there were no available fiducials. Therefore, only the SRE was measured. The number of points used in the US surfaces was choosen 3500. The proposed method was able to register the three clinical radius scans with a mean SRE of 0.66 mm (SD=0.72 mm) using the Poisson surface reconstruction .

IV. CONCLUSION

We have presented an ultrasound-based registration method for minimally invasive computer-assisted long bones surgery. We introduced the Poisson surface reconstruction method to solve the problem of thickness and non-uniform points distribution in the initial US point cloud. Our proposed surface reconstruction guides better the registration between the two volume modalities and gives lower registration error than using the US bone point cloud directly acquired from the 2D tracked US probe.Validation experiments were conducted on phantom as well as clinical data. The procedure is full automatic, real time and does not require any human

interaction. The proposed method showed promising and accurate results even in the case of bad initial alignment. But, its use in the clinical procedures rerquires more clinical experiments. However, more effort should be done in order to validate the outlier weightening proposed method.

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