Surface based US/MeVis-CT registration for open liver surgery

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Abstract:
Recent progress in computer science enables the use of instrument guidance systems for open liver surgery. However, challenge remains when precise alignment between the pre-operative image data and the intra-operative situation is required, since the liver is subject to deformation and movements during the surgical treatment. Fusion of intra-operative navigated US with the pre-operative data is one of the solution to improve this situation. We present here a clinically applicable method to automatically refine the registration between the pre- and intra-operative data based on US/MeVis-CT registration. Evaluation done on clinical data showed that in a pre-defined region of interest, using this framework, a registration error smaller than 7mm is reached.

Keywords: Liver Surgery, Registration, Ultrasound

1 Problem

Recently, navigation systems for liver surgery have been developed and are now commercially available (CAS-One liver navigation system (CAScination, AG, Switzerland) and Explorer Liver (Pathfinder Therapeutics)). Navigation systems provide improved orientation and guidance support during planning and surgery. Precise alignment between pre-operative image data and intra-operative situation remains challenging as the liver deforms during the surgery. Navigated intra-operative ultrasound (US) provides detailed information about internal organ structures and thus might allow more accurate pre- to intra-operative data registration. Higher precision in navigated surgery will enable the use of smaller safety margin to preserve more healthy tissue.

The CAS-One liver navigation system applies a landmark based registration to perform the alignment. A recent study [1] shows that using this technique a mean registration error of 9mm can be reached with a mean time requirement of 90s. Thus, this method can reliably be used as an initial alignment to the US/CT refinement registration framework. In [2], to overcome the overall non-rigid deformation between the pre- and intra-operative data, the authors propose to focus on localized region in which a rigid alignment will give a satisfactory accuracy for local navigation. Based on our former experience in navigated liver surgery and following their suggestions on local navigation, we decided to use a rigid registration in a local site of interest and aim at having a mean registration error smaller than 7mm in it.

Requirements for a clinically applicable framework are to be reliable, fast, automatic and easy to use. Many methodologies have been proposed in the literature to register US to pre-operative data, a review on those methods for liver surgery can be founded in here [3]. CAS-One liver navigation system contains a set of plugins to enable the loading of different types of surgical planning data. In the case of a planning done with MeVis distant services and a CT scan, the pre-operative data available are the CT greyscale images (3 phases), the segmentation masks of the CT structures (liver surface, hepatic and portal veins, metastasis and/or tumors) and the surface models of the structures. In respect to that, due to previous works done on vessel segmentation [4] and due to the computational efficiency of feature-based registration methods, we decided to base our registration technique on feature-based registration with segmented vessels as single feature. Here we evaluate two point based registration algorithms, the well-known iterative closest point (ICP [5]) and a stochastic global optimization for robust point-based registration (GBSP [6]).

Within this paper, we present our solution to automatically refine the initial alignment by applying an US to CT based registration. We provide first a description of the solution, then qualitative and quantitative evaluations of the registration algorithms.

2 Methods

A. Solution Proposal

US/CT registration framework starts with a landmark-based alignment aiming for a registration error smaller than 20mm. Then, the region of interest (ROI) is defined interactively by moving the navigated US probe onto the patient liver. The prospective ROI is displayed by a virtual yellow box which is placed below the virtual US probe. The yellow box delimited the region in which the rigid alignment will be performed. The acquisition starts by holding the probe onto the ROI. Incoming US images are segmented and compounded in real time to create a 3D US model of the vessels. Once the acquisition is completed, the registration is performed.

B. Segmentation

The segmentation algorithm applies the method described in [4]. It consist of a multi-scale algorithm proven to be independent to US parameters. The segmentation algorithm has a detection rate of 80% for vessels having a diameter larger than 3mm. To incorporate the segmentation algorithm into the framework (real time acquisition, segmentation and compounding), the computation of the scaled images was implemented onto the GPU.

C. Registration

The two registration algorithms evaluated here are the iterative closest point algorithm (ICP [5]) and a stochastic global optimization for robust point based registration (GBSP [6]). The ICP minimizes the distance between corresponding points in two point clouds. The algorithm's key advantage is its usability in real-time. The major algorithm drawback is its tendency to converge to local minima. The VTK implementation of the ICP algorithm was incorporated to the CAS-One liver system using a maximum number of iterations of 200 and 2000 landmarks. The GBSP algorithm used here is an adaptive sampling method which uses a generalized binary space partition (GBSP) tree. The main algorithm advantages are noise robustness, outlier resistance and global optimal alignment. A homemade VTK implementation of the algorithm was incorporated to the CAS-One liver system using the parameter sets described in [6] expect the maximum number of iterations (200) and the number of landmarks (2000).

To validate the usability of such algorithms, we tested them on real data.
25 US sweeps and corresponding MeVis-CT were collected during open liver surgery of 3 patients (Table 1). The following offline evaluation was performed:

a. Visual Inspection: Segmentation, compounding and registration success were visually assessed. Segmentation was considered as failed if no vessels were acquired or if large artifacts were compromising the segmentation algorithm. Compounding was considered as failed if no structures were visually identifiable (vessels, vessel branches). Registration was considered as failed if the algorithm converged to a wrong position.

b. Registration error: Datasets were manually segmented (MS) and aligned (MA) to create a ground truth. The manual alignment was repeated 3 times per dataset and averaged. Different combinations of segmentation and registration algorithms were then applied and compared to the ground truth:

(1) Manually segmented and automatically registered with ICP (MS+ICP).
(2) Manually segmented and automatically registered with GBSP (MS+GBSP).
(3) Automatically segmented and automatically registered with ICP (AS+ICP).
(4) Automatically segmented and automatically registered with GBSP (AS+GBSP).

The experiments 1) and 2) use an optimal segmentation and are therefore specifically evaluating the performance of the registration algorithms whereas 3) and 4) are validating the entire automatic segmentation and registration workflow.
The distance between corresponding points in the ground truth dataset and the registered one was used as error measure (correspondence between points on two identical segmented surface meshes avoids errors introduced by correspondence finding). Errors are reported for the region of interest (ROI) where ultrasound data was acquired (=surgical site of interest) and on the entire liver.

c. Runtime measurement: The time for executing the entire registration framework was measured as well as the processing time of the ICP and GBSP algorithms.

3 Results

a. Visual Inspection: 56% percent of the dataset succeed the segmentation criteria. Lack of vessel information was the principal reason of failure (33%). Over segmentation was the second reason of failure (8%). Out of the 56% of successfully segmented datasets, 85% were correctly compounded. Impossibility to visually identify the corresponding CT structures was the main reason of failure. Out of the successfully compounded data, visually correct registration was ob-

tained in 75% for the ICP and 83% for the GBSP. In total, if we combine all the steps, US/CT based registration framework was successful in 37% of time for the ICP and 41% for the GBSP.
b. Registration error: From the 25 datasets acquired during surgery, we selected 5 which passed the visual inspection criteria. We manually segmented and registered these 5 datasets. Table 2 shows the mean, min and max measured registration errors inside the ROI. Figure 1 illustrates the registration error maps onto the surface of the vessels obtained from one dataset (MS+GBSP). Inside the ROI, the registration error is inferior to 7mm. The measured registration error was lower for manually segmented data than for automatically segmented data for both, ICP and GBSP algorithms (MS+ICP: 6.3mm AS+ICP: 7.36mm and MS+GBSP: 3.7mm AS+GBSP: 6.14mm). We observed, for both manual and automatic segmentations a higher performance of the GBSP algorithm: For manual segmentation, the datasets had always a mean registration error smaller than 7mm. For automatic segmentation, 4/5 datasets had a mean registration error smaller than 7mm.
c. Runtime measurement: In average, the entire framework (from the acquisition to the registration) requires 49 seconds (min: 15s max: 90s). The average processing time for the ICP was 5.2 seconds and 10.6 seconds for the GBSP.

4 Discussion

We presented here an entire framework to refine the initial alignment between pre- and post-operative data based on US/CT registration. The proposed solution consists in four main steps: (1) Initial alignment; (2) site of interest selection (e.g. a tumor to ablate); (3) intra-operative acquisition with real-time segmentation and compounding; and (4) automatic registration refinement.
Results demonstrate the higher performance of the GBSP compare to the ICP. Visual inspection of results on real data shows that the current solution will improve the initial registration in 83% (For the GBSP, 75% for the ICP) of the cases if ultrasound data is correctly acquired. The number drops to 41% of the cases when segmentation or compounding is included in the evaluation. We expect that ensuring a valid acquired US dataset will provide more reliable registration results.
Mean registration error for manually segmented/registered data (ICP: 6.3mm, GBSP: 3.7mm) is lower than for automat-

ically segmented/ registered data (ICP: 7.3mm, GBSP: 6.1mm). It clearly shows the predominant effect of segmentation onto registration results. We expect that improving the segmentation will improve the US/CT registration framework outcomes. With a perfect segmentation, we can reach a mean registration error of 3.7mm inside the ROI (currently we have 6.1mm). As a next step, additional evaluation on the influence of US image quality (cirrhosis, sterile cover) will be performed.

We obtained a success rate of 83% with the GBSP if data are correctly acquired. We also showed that the segmentation algorithm has a direct impact on the registration algorithm outcomes. Finally we demonstrate that using this framework, the registration error in smaller than 7mm in a ROI. We will further investigate the following topics: (1) Evaluating the influence of US image quality on registration outcomes; (2) Incorporate additional prior information to the registration algorithm to reduce the number of failure and/or to indicate registration success or failure; (3) Manually segment and register more datasets to evaluate systematically the US/CT based registration framework versus a ground truth.

	Fiducial landmark (LM) positioning		Number of sweep	FRE	Clinical information	
					Number of lesions	Tumor location
Patient 1	*LM1*	Middle hepatic vein	13	16.1mm	13	bilobar
	LM2	Fissure of the falciform ligament				
	LM3	Portal vein 1st order bifurcation				
	LM4	Portal vein 2nd order bifurcation right lobe				
Patient 2	*LM1*	Middle hepatic vein	6	7.1mm	18	bilobar
	LM2	Fissure of the falciform ligament				
	LM3	Surface of tumor right lobe				
	LM4	Surface of tumor right lobe				
Patient 3	*LM1*	Middle hepatic vein	6	14.6mm	2	unilobar, segment 7
	LM2	Fissure of the falciform ligament				
	LM3	Cross of the portal vein				
	LM4	Gallbladder Bed				

Table 1. Description of the acquired data. Fiducial Registration Error (FRE).

Inside ROI

	Manual Segmentation		Automatic Segmentation	
	ICP Mean (Min Max)	GBSP Mean (Min Max)	ICP Mean (Min Max)	GBSP Mean (Min Max)
Dataset 1	16.2 (9.9:27.7)	**3.3 (0.3:8.4)**	8.9 (5.9:12.3)	11.9 (7.1:17.5)
Dataset 2	**3.3 (0.1:8.3)**	**3.4 (0.1:8.3)**	8.0 (3.7:17.4)	**4.8 (2.4:10.2)**
Dataset 3	**5.1 (1.5:11.8)**	**5.0 (1.6:11.4)**	10.5 (0.8:19.7)	**6.8 (1.1:14.2)**
Dataset 5	**3.6 (1.1:8.2)**	**4.0 (3.7:4.3)**	**6.5 (3.5:11.9)**	**4.3 (0.9:6.9)**
Dataset 6	**3.1 (0.7:7.4)**	**3.1 (0.7:7.4)**	**2.9 (1.1:7.0)**	**2.9 (1.1:7.0)**

Table 2. Mean, min and max measured registration error inside the ROI. Values denoted in bold have a mean registration error smaller than 7mm.

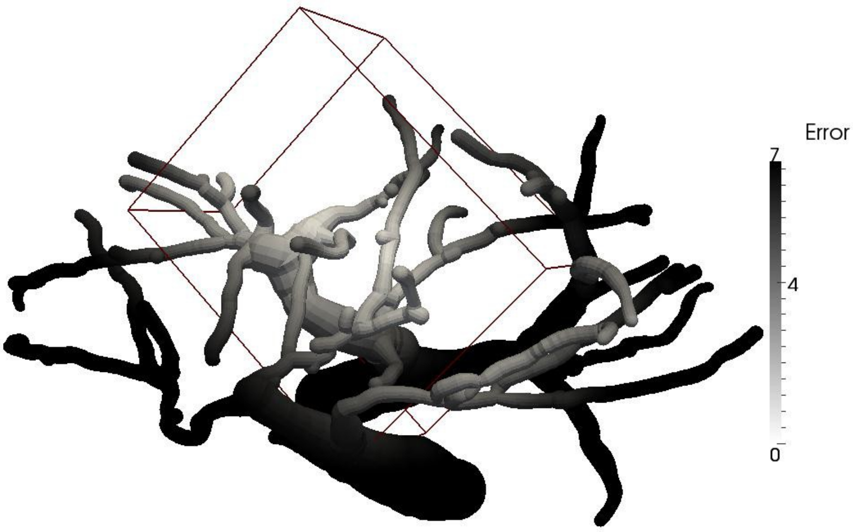

Figure 1. Registration error map onto the vessels of the CT dataset for the dataset 1 (MS+GBSP). The box delineates the ROI. Inside the ROI, the registration error is smaller than 7mm.

5 References

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