Combining Visual Cues and Interactions for 3D-2D Registration in Liver Laparoscopy

Yamid Espinel, Erol Özgür, Lilian Calvet,
Bertrand Le Roy, Emmanuel Buc, and Adrien Bartoli

EnCoV, IP, UMR 6602 CNRS / UCA, CHU Clermont-Ferrand

1 Purpose

One of the main current limitations of laparoscopy is the difficulty to accurately localize the target organ's internal anatomy, owing to the absence of tactile feedback. This is a particularly important issue for the liver, which may contain malignant tumours to be precisely resected with an oncologic margin. Augmented Reality (AR) is a promising approach to overcome this limitation. The key idea is to overlay information extracted from a preoperative CT or MR volume onto the laparoscopy images. This extracted information may contain the tumours but also the vascular structures. Technically, this requires one to align or *register* a preoperative 3D model to the laparoscopy image. This is a very challenging and currently highly researched problem [1–4]. We focus on regular laparoscopy, which in terms of computer vision is a single monocular pin-hole camera, and forms the standard in operating theatres.

The state-of-the-art registration methods are either *manual* [4] or *automatic* [1–3]. In [4], the preoperative 3D model is rigidly registered to the laparoscopy image by means of user interaction. In [1–3], the preoperative model is deformed following a biomechanical model via an ICP-like procedure to fit visual cues extracted from the laparoscopy image. These visual cues are anatomical landmarks including the falciform ligament and the inferior ridge, and the silhouette. The current manual and automatic approaches both present important shortcomings, illustrated in figure 1. In [4], the rigidity assumption is far too restrictive to accurately model the liver deformation. In [1–3], the visual cues are sparse and do not convey enough information to unambiguously constrain registration. Though the reasons are different, this results in both cases in misregistration, impairing the reliability of AR.

2 Methods

We propose a *hybrid* registration approach. The key idea is that the manual and automatic approaches are highly complementary. Our hybrid approach combines user interaction with visual cues and a biomechanical model. In the presence of both user interaction and visual cues, our hybrid approach bundles all constraints in a single registration. In the absence of user interaction, it behaves similarly to

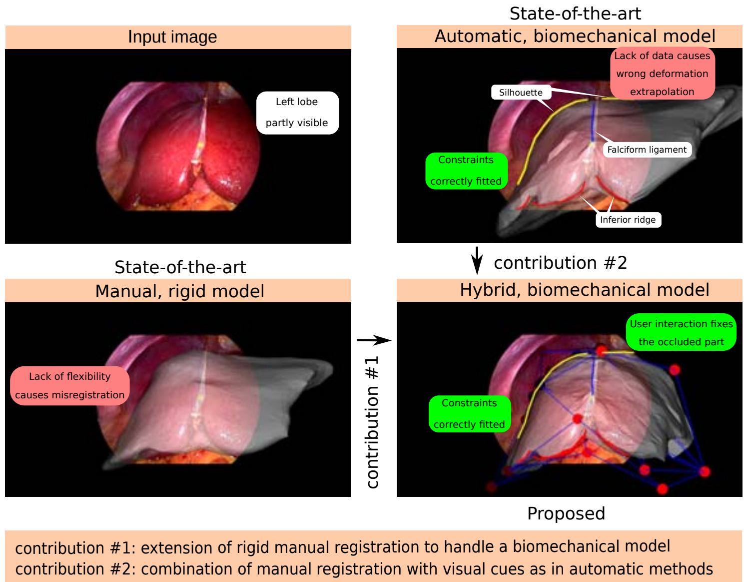

Fig. 1. Registration results delivered by the state-of-the-art methods and the proposed one. (top left) The input laparoscopic image. (top right) Results from the automatic method [1] based on visual cues (contour constraints in yellow, blue and red). (bottom left) Results of the manual rigid registration method [4]. (bottom right) Results of the proposed hybrid method, combining visual cues with a biomechanical model through cage-based tactile interaction. The cage's control points (red dots) are used to deform the preoperative 3D model.

the existing automatic approaches, while in the absence of visual cues, it allows the user to edit the registration under guidance of the biomechanical model. This is a significant improvement compared to the existing manual approach as it allows the user to fully express their expertise in anatomy, prior experience and spatial understanding of the case at hand to the system. We have implemented this idea following the cage-based paradigm from the field of shape editing. The cage may be seen as a set of draggable control points enclosing the organ. Shape editing is a widely studied problem, to which the main proposed approaches are point-based [5], curve-based [6], surface-based [7] and cage-based [8]. The cage-based paradigm is well-adapted to registration owing to its flexibility. Concretely, we implemented our hybrid method with a Qt Graphical User Interface (GUI) shown in figure 2. Our system is entirely controllable by tactile interaction and may be used in a fast and intuitive manner.

3 Results

We compared our method named *hybrid biomechanical* (HB) quantitatively in two ways against two previous methods [4], named *manual rigid* (MR) and

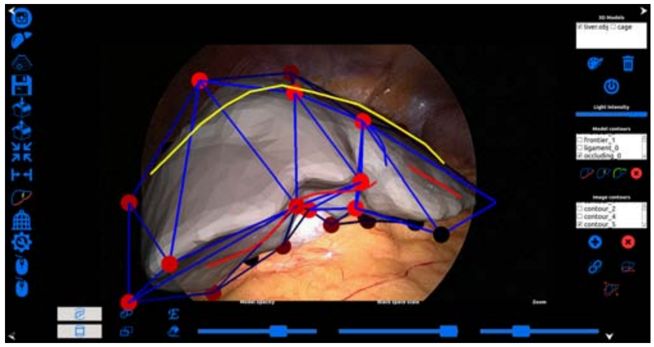

Fig. 2. Proposed Qt graphical interface: the left toolbar contains tools for loading the laparoscopic image and the preoperative 3D model, exporting and importing the entire scene, and generating the 3D cage; the right toolbar contains tools for managing the 3D model, image and model's contours, and launching the registration; the bottom toolbar contains tools for zooming, editing the model's transparency and shape.

[1], named *automatic biomechanical* (AB). The first evaluation uses a silicone liver phantom faithfully reproducing the shape of a patient's liver obtained from CT reconstruction. The phantom was deformed and we used Structure-from-Motion to reconstruct its 3D shape ground-truth [9]. The registration was then tested for 20 views from 4 different deformation datasets (5 views per dataset). The registration error, defined as the average distance between vertices of the preoperative and ground-truth models, is reported in figure 3(a). The registration error was evaluated for the visible and hidden parts. The second evaluation uses 8 images from 8 patients and had registration solved by our system under the control of 8 surgeons. The registration variability, defined as the root mean square of the stantard deviation of the vertex positions, was evaluated for the visible and hidden parts. It is reported in figure 3(b).

4 Discussion and Conclusion

For the phantom data, HB shows the lowest registration error, well below 1 cm. The error of MR is noticeably high, generally greater than 1 cm, showing that the deformation is significant. The registration error of AB is overall lower than MR's. The visual cues in AB thus sufficiently constrain the biomechanical model. HB shows decreased registration error thanks to the possibility of correcting the misaligned parts while respecting the anatomical and biomechanical constraints.

For the patient data, the variability across different users is of 7.79 mm on average which shows that HB passes the requirement of a low variability. The image of patient 4 was far more challenging than the others due to a lack of visibility of the liver, explaining its high variability.

The phantom data show that the average registration error is of 5.83 mm for the whole liver and 5.53 mm for the visible parts with our hybrid method

Registration error for whole liver (mm)				Registration error for visible part (mm)			
Dataset ↓	MR	AB	HB	Dataset ↓	MR	AB	HB
1	09.00	05.35	04.10	1	11.09	07.96	04.62
2	06.19	08.65	05.05	2	06.77	07.78	04.11
3	12.23	10.32	08.46	3	12.67	09.43	05.60
4	08.60	06.78	05.70	4	10.46	06.67	07.80

(a)

Patient →	1	2	3	4	5	6	7	8
Whole liver	07.05	11.19	12.23	20.33	08.12	08.63	12.34	08.01
Visible	06.95	11.09	08.12	15.66	05.52	04.50	06.26	04.19
Tumour	05.99	10.83	07.24	18.77	04.19	03.37	09.00	08.63

(b)

Fig. 3. (a) Registration errors for the phantom data. (b) Registration variability (in mm) of three sets of model parts for the patient data.

HB. This is very promising as being below the 1 cm oncologic margin advised in the literature for tumour resection in laparoscopic hepatectomy. However, further clinical tests have to be made in order to validate our method, notably regarding the location of inner structures such as tumours and vessels after registration. If such tests confirm an overall registration error lower than 1 cm, then the proposed method will give surgeons a reliable basis to guide resection. In future work, it will also be important to estimate the registration uncertainty and to relate it to the registration error to discard ill-constrained cases such as the image of patient 4 automatically.

References

1. Koo, B., Ozgur, E., Le Roy, B., Buc, E., Bartoli, A.: Deformable registration of a preoperative 3D liver volume to a laparoscopy image using contour and shading cues. MICCAI, (2017)
2. Haouchine, N., Roy, F., Untereiner, L., Cotin, S.: Using contours as boundary conditions for elastic registration during minimally invasive hepatic surgery. IROS, (2016)
3. Adagolodjo, Y., Trivisonne, R., Haouchine, N., Cotin, S., Courtecuisse, H.: Silhouette-based pose estimation for deformable organs application to surgical augmented reality. IROS, (2017)
4. Nicolau, S., Soler, L., Mutter, D., Marescaux, J.: Augmented reality in laparoscopic surgical oncology. Surgical Oncology, 20 3, 189-201 (2011).
5. Bechmann, D. and Gerber, D. 2003. Arbitrary shaped deformations with dogme. The Visual Computer, 19, 175-186. (2003)
6. Barr, A. H. Global and local deformations of solid primitives. Computer Graphics (SIGGRAPH 84), 18 3, 21-30. (1984)
7. Feng, J., Shao, J., Jin, X., Peng, Q., and Forrest, R. Multiresolution free-form deformations with subdivision surfaces of arbitrary topology. The Visual Computer, 22 1, 28-42. (2005)
8. Sederberg, T. W. and Parry, S. R.: Free-form deformation of solid geometric models. SIGGRAPH, (1986)
9. AgiSoft PhotoScan Professional (Version 1.2.6) (Software).