Feasibility of Online Semantic Labeling of Deformable Tissues for Minimally Invasive Surgery[1]

John J. O'Neill
Department of Mechanical Engineering,
University of Minnesota,
Minneapolis, MN 55455

Timothy M. Kowalewski
Department of Mechanical Engineering,
University of Minnesota,
Minneapolis, MN 55455

Robert M. Sweet
Department of Urology,
University of Minnesota,
Minneapolis, MN 55455

1 Background

Vascular injury accounts for one third of complications in laparoscopy [1]. It is the second highest cause of death within laparoscopic surgery, second only to anesthesia, with a mortality rate estimated at 15% [2]. Surgery is also extremely common, currently surgeries are performed at a rate of 50 million per year, giving the average American an expected seven surgeries in their lifetime [3]. There is currently no way to (1) detect imminent vascular injury during surgery (2) prevent it via alarm or possibly an automated emergency stop in the case of a surgical robot.

Surgical robots have become increasingly popular. However, they remain a passive master–slave system with no safeguards for adverse events like vascular injury. In the past, this is because the robotic systems do not have sufficient means of (1) tracking deformable tissues during surgery and, crucially, (2) semantically labeling the tracked data; e.g., blood vessel to protect versus kidney tissue to resect.

Time of flight cameras have been proposed for tracking tissue geometry through an endoscope [4]. We herein propose to use time of flight to track and semantically label tissues in real time. Specifically, we evaluated the feasibility of time of flight tracking for semantically distinguishing kidney tissue from connected vasculature in real time using a modified algorithm.

2 Methods

2.1 Time of Flight. Time of flight works by sending a modulated laser signal and measuring the phase shift of the returned signal. This phase shift in time is then multiplied by the speed of light to get the distance to and from the object, e.g., if the signal was delayed 1 ns, the flight distance would be 30 cm, or the object would be 15 cm away [5].

2.2 Iterative Closest Point (ICP). A method of aligning semantic point based data sets, the ICP algorithm does not require any feature recognition. It simply looks to minimize the distance between each point in set A with the distance to the closest point in set B, addressing the correspondence problem by assuming that the closest points correspond [6]. This is then iterated, since the closest points may have changed, until a target distance or number of iterations is reached. This algorithm has a computational complexity of $\mathcal{O}(N_A \log(N_B))$ due to the need for finding nearest neighbors.

2.3 Local Rigid Transformation. Points are clustered into groups of similar transformation, allowing the total representation to vary up to a separate transformation for each point, but down to a small number of bins each with its own rigid transformation.

This can be modified by segmenting the prior data (e.g., MRI data) during the same process as identifying the organs/regions. Then the prior data are matched to the current scan data, instead of the other way around, with local rigid transformations. The prior data can also be segmented in nested decreasing sizes, e.g., organ level, organ quadrant, etc.

2.4 Experimental Setup. The system uses a time of flight depth camera sensing an artificial 3D printed organ in association with a prior data medical data to determine the location of the end effector with respect to the dangerous areas of the body and several nonrigid registrations will be tested to evaluate real-time performance.

The time of flight depth camera used was a DepthSense 325 (SoftKinetic, Brussels Belgium) [7]. The depth sensor is a OPT8140 chip (Texas Instruments Inc., Dallas Texas) with a quarter video graphics array, 320×240 resolution.

The synthetic organ and vasculature were provided by the Center for Research in Education and Simulation Technologies (CREST) at the University of Minnesota. The analogue prior medical data for this experiment were a prior scan with the same equipment, manually segmented into organ and vasculature.

The experiment consisted of taking an initial scan of the pliable synthetic organ (kidney and surrounding vasculature), then deforming the organ, and then rescanning with time-of-flight scanner and evaluating whether the Local Rigid Transformation provided an improvement over the rigid transformation. The experimental setup can be seen in Fig. 1.

The experimental algorithm consists of calling the ICP once for the global level, and then for each semantically labeled subitem, which consists of the kidney and the surrounding vasculature. The algorithm has a computational complexity of £ $(N_A \log(N_B))$ and scales linearly with the number of levels in the semantic tree. An algorithm listing can be seen in Algorithm 1.

3 Results

The first ICP with rigid transformation provided gross positioning and orientation as can be seen in the top row of Fig. 2.

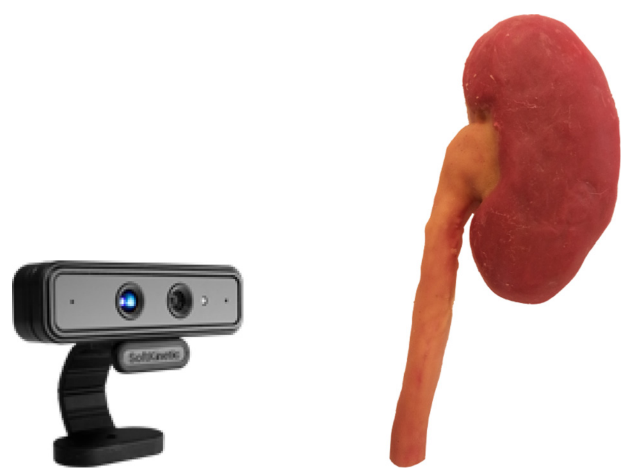

Fig. 1 Experiment setup: time of flight camera and synthetic kidney

[1]Accepted and presented at The Design of Medical Devices Conference (DMD2015), April 13–16, 2015, Minneapolis, MN, USA.

DOI: 10.1115/1.4030570
Manuscript received March 3, 2015; final manuscript received March 17, 2015; published online July 16, 2015. Editor: Arthur Erdman.

Algorithm 1 Experimental Algorithm

```
DATA SEGMENTATION(ReferencePointCloud)
for each level in the semantic tree do
  for each item in the level do
    // Find a rigid transformation that is in addition
    // to the rigid transformation of the parent
    ITERATIVE CLOSEST POINT(TargetSeg,Reference)
    POST-REGISTRATION(Transformation)
  end for
end for
```

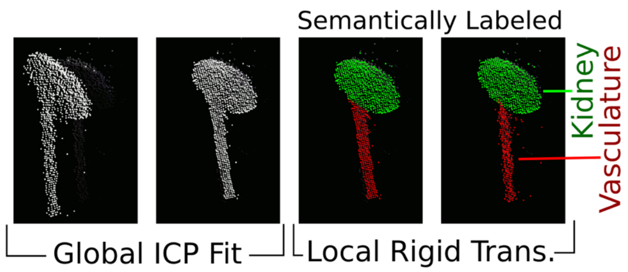

Fig. 2 Results with semantically labeled tissues

The next layer of ICP was calculated for each separate anatomy piece, and the resultant fit can be seen in Fig. 2, with the kidney at the top of the image and the vasculature at the bottom. This provided an improved fit for the model and semantically labeled the vasculature and kidney based on mapping from prior data.

4 Interpretation

Matching results show the ability to match both global and local features with local rigid transformations with a time of flight camera. Most importantly, this approach retains semantic labeling of the anatomical regions after deformation. For future work, additional algorithms will be tested and evaluated for robustness, fit, and speed, and additional hard ware will be developed to test the algorithms through an endoscope.

References

[1] Mases, A., Montes, A., Ramos, R., Trillo, L., and Puig, M. M., 2000, "Injury to the Abdominal Aorta During Laparoscopic Surgery: An Unusual Presentation," Anesth. Analg., **91**(3), pp. 561–562.
[2] Philips, P. A., and Amaral, J. F., 2001, "Abdominal Access Complications in Laparoscopic Surgery," J. Am. Coll. Surg., **192**(4), pp. 525–536.
[3] Gawande, A., 2012, "Two Hundred Years of Surgery," N. Engl. J. Med., **366**(18), pp. 1716–1723.
[4] Penne, J., Höller, K., Stürmer, M., Schrauder, T., Schneider, A., Engelbrecht, R., Feußner, H., Schmauss, B., and Hornegger, J., 2009, "Time-of-Flight 3-D Endoscopy," *Medical Image Computing and Computer-Assisted Intervention—MICCAI 2009*, Springer, Berlin, pp. 467–474.
[5] Texas Instruments, 2013, "Introduction to the Time-of-Flight (TOF) System Design: User's Guide," Technical Report SBAU219D.
[6] Besl, P. J., and McKay, N. D., 1992, "Method for Registration of 3-D Shapes," Proc. SPIE, **1611**, pp. 586–606.
[7] Cree, M. J., Streeter, L. V., Conroy, R. M., and Dorrington, A. A., 2013, "Analysis of the SoftKinetic DepthSense for Range Imaging," *Image Analysis and Recognition*, Springer, Berlin, pp. 668–675.