Tissue Identification Through Back End Sensing on da Vinci EndoWrist Surgical Tool[1]

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1 Background

Surgical robots are becoming more common in the operating room. Although surgeons utilize these robots for improved dexterity, scalable movements, and enhanced vision, they lose their sense of tactile and haptic feedback [1]. Okamura demonstrated a negative consequence of this by showing that forces exerted during robotic sutures significantly exceed that of hand sutures [2]. This excess in force can lead to a variety of complications including tissue crushing, which has been shown to be a clinically relevant problem [3].

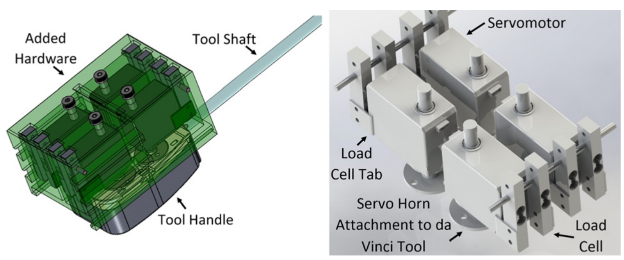
Sie et al. proposed tissue-aware grasping as a solution for tissue crush injury, which may obviate the need for tactile and haptic feedback altogether [4]. By coupling online tissue identification with tissue-specific thresholds for crush injury, the surgical robot can warn of imminent tissue crushing or potentially prevent it. Sie et al. provided relevant work in this area by validating an approach for online tissue identification within the first 0.3 s of a grasp. This work was done with a modified manual laparoscopic Babcock grasper; this is a specialized instrument not commonly used in surgery. We herein aim to extend the results of Sie et al. to a much more common surgical tool: the da Vinci EndoWrist surgical instrument (Intuitive Surgical, Sunnyvale, CA). We demonstrate that tissue identification is possible using existing robotic tools without additional sensors or modifications to the tool tip, by using only motor torque and position data at the proximal end of the tool.

2 Methods

This work represents two components: mechatronic design of the standalone attachment compatible with the da Vinci EndoWrist and experimental validation of our approach on synthetic tissues.

2.1 Mechatronic Design. The existing da Vinci EndoWrist consists of three components: the handle, the shaft, and the tool tip. Our entire mechatronic design interfaces with only the handle; no modifications or sensors were added to the tool shaft or tip. The EndoWrist handle contains four spindles, which provide separate control over both tool jaws, as well as roll and pitch of the tool. Our attachment interfaces directly with these spindles. Connected to each spindle is a servomotor (HS-422 HiTec, South Korea). Micro load cells are placed to measure the servomotor's applied force and hence spindle torque (3132 Micro Load Cell CZL616C, Phidgets Inc., Calgary, AB, Canada). A microcontroller (Arduino UNO ATmega328, Arduino, Italy) synchronously samples servomotor potentiometer readings and load cell data through custom circuitry. This circuit consists of a low pass RC filter with a cutoff frequency of 10 Hz and differential amplifiers (AD623, Analog Devices, Norwood, MA). The microcontroller streamed time-stamped data over serial connection at approximately 100 Hz and saved this data directly to a file. A 3D printed acrylonitrile butadiene styrene housing encases all of these mechatronic components. A transparent view of the mechatronic design along with a view of the internal servomotors and load cells are shown in Figs. 1(*a*) and 1(*b*), respectively.

2.2 Experimental Protocol. The system was tested on seven synthetic tissue analogs (SimPORTAL, University of Minnesota) in order to test whether it can distinguish tissue types (Fig. 2). Tissues were grasped in a manner similar to Ref. [5]. During grasping tests, data from one spindle drive unit (SDU) were collected. An SDU consists of one da Vinci EndoWrist spindle actuated via servomotor. The microcontroller repeatedly commanded a slow, controlled grasp. The servomotor followed a ramp trajectory from a fully open to fully closed position over approximately an 8.9 s duration. Displacement data from the potentiometer and force data from the load cell were collected during the grasping process. The data from the loading portion of the grasp were fit using a nonlinear least squares fit (Fig. 3) to the simplified Fung model [5] using MATLAB (Mathworks, Natick, MA). Following the findings of Ref. [5] for tissue behavior, the constitutive model for



(a) Transparent view of device (b) Internal hardware components

Fig. 1 External and internal views of design. (*a*) Transparent view of device and (*b*) internal hardware components.

Fig. 2 Synthetic tissues used in experimentation

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

DOI: 10.1115/1.4030571

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

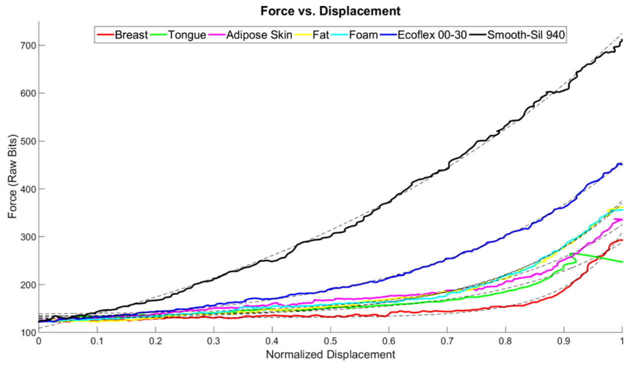


Fig. 3 Experimental data with overlaying least squares fit

quasi-static compressive loading is as follows, with α, β, and c as model parameters:

$$\sigma = \alpha(e^{\beta\varepsilon} - 1) + c$$

Constant values for each model parameters were extracted from the least square fits.

3 Results

Values for α, β, and c are tabulated for each of the synthetic tissues in Table 1. There is a general increase in α values and decrease in β values as tissue hardness increases. The value for c remains fairly constant for each material.

4 Interpretation

The values in Table 1 indicate that each tissue has unique model parameter values. This shows that discrimination of the various tissues is possible with our method. Similar to Sie et al., our work provides proper means for tissue identification. However, our method requires no modifications to the tool tip, and the work applies to a much more common surgical robot. By eliminating modifications to the tool tip, this work can more effectively transition into the operating room. Our back end sensing approach eliminates any need for our device to enter the human body, thus future work will extend to in vivo experiments.

This research is additionally useful because our method is compatible with the da Vinci robot, which is a common platform for robotic surgery. In principal, this work can be extended to online tissue identification via Kalman filtering as demonstrated by Sie et al. This is a necessary step for full implementation of a tissue-aware grasper for detection and prevention of tissue crush injury. All future work validated on this research tool can readily extend to the existing surgical robot.

Table 1 Results of least squares fit

Tissue	α	β	c	R^2
Breast	6.19×10^{-3}	10.27	131.2	0.983
Tongue	1.21	4.84	134.6	0.962
Fat	2.06	4.52	139.1	0.971
Adipose skin	2.07	4.76	129.5	0.993
Foam	1.48	5.11	133.8	0.990
Ecoflex 00–30	17.83	2.96	128.5	0.999
Smooth-Sil 940	201.70	1.40	109.0	0.999

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