Feasibility of Tissue Classification via da Vinci EndoWrist Surgical Tool

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INTRODUCTION

Robot-assisted minimally invasive surgery has gained popularity over the past few decades. With the introduction of robotic equipment in the operating room comes a wealth of sensory data inherent to the robot. Yet much of this rich data remains underutilized. One potential application is found in creating tissue-aware surgical robots. Sie et al. have shown that tissue-aware surgical robots are possible via tissue identification in real-time during tissue grasping [1]. This would enable tissue-aware robots to avoid surgical errors such as tissue crush injury [2].

The objective of this study is to determine whether existing data streams for a popular tool like the da Vinci® EndoWrist® can be used to identify grasped tissue. We employ cadaveric human tissues.

MATERIALS AND METHODS

A custom mechatronic setup with a da Vinci® EndoWrist® surgical grasper was utilized for all cadaveric tissue data collection (Fig. 1). The mechatronic device measures both force and position throughout the grasp using load cells and potentiometers, respectively. These measurements are taken at the spindles on the proximal end of the tool as to not disturb the distal grasping end and provide a surrogate for the torque (motor current) and position (encoder counts) already present in the da Vinci® control loop. The mechanical hardware is described in [3]. The electrical hardware was upgraded to include a 24-bit analog-to-digital converter (ADC) for the load cell data, and a 12-bit ADC on a 32-bit microcontroller for the potentiometer data.

Two different cadaveric tissues were grasped along with their surrounding adipose tissue; this resulted in a total of four distinct data sets: kidney, pancreas, kidney adipose, and pancreatic adipose. The tissues were refrigerated and stored at 2°C in 0.09% saline for the pancreas (Fisher Scientific) and KPS-1 for the kidney (Organ Recovery Systems) and all tissues were tested within one week post-mortem. The tissues were removed from refrigeration and data collection immediately began in a room temperature environment. The outside of each organ was grasped repeatedly with the mechatronic device. Data collection on each tissue type occurred with da Vinci® EndoWrist® Maryland Bipolar Forceps.

Position and force data were collected at 1kHz with each grasp lasting approximately 400ms. In total 32 kidney, 12 pancreas, 22 kidney adipose, and 10 pancreatic adipose grasps were collected.

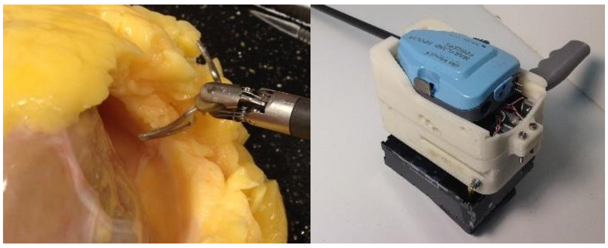

Fig. 1 Experimental setup, showing kidney with surrounding adipose tissue on the left and the mechatronic setup on the right.

Tissue discrimination was achieved using a least squares approach for model training and an error ratio method for online classification. The tissue model used was originally proposed by Yu et al. [4]:

$$u = M\ddot{p} + D\dot{p} + \alpha(e^{\beta p} - 1) \qquad (1)$$

Here u represents the grasper force and p is the grasper angle. In order to utilize this model in a least squares method, the nonlinear term $(\alpha(e^{\beta p} - 1))$ is expanded into a second order polynomial $(k_1\epsilon + k_2\epsilon^2)$. Force (u) and angle (p) are expressed in terms of tissue stress (σ) and strain (ϵ) with constants (m and d) changed to reflect appropriate units.

$$\sigma = m\ddot{\epsilon} + d\dot{\epsilon} + k_1\epsilon + k_2\epsilon^2 \qquad (2)$$

With this model, the training data is then used to compute least squares parameter sets for each tissue type:

$$\Phi_i = [m, d, k_1, k_2] \qquad (3)$$

With these parameter sets computed for each class, online classification is achieved by computing the model error between the current data (σ) and the ith linear model:

$$E_i(t) = \|\sigma(t) - X(t)\Phi_i\| \qquad (4)$$

Where X is the sample data at a given time step:

$$X(t) = [\ddot{\epsilon}(t), \dot{\epsilon}(t), \epsilon(t), \epsilon(t)^2] \qquad (5)$$

Given the model errors for each tissue type, the online tissue is classified by finding the tissue with the lowest cumulative model error at a given time step.

A leave-one-out classification scheme was used for each grasp segment of eash tissue type resulting in 66 total online grasps. This classification followed a binary pairwise approach.

The data were filtered with a 4th order Butterworth filter using a 4Hz cutoff frequency. Since we measured position but the independent variable in our tissue model is strain (Eq. 2) we estimated strain by calculating change in position (p), where the position was re-zeroed at the first touch of the grasp. We found the position of first touch in post-processing by determining the center of the range of force data, and then moving forwards and backwards in time to the limits.

We estimated stress by measuring force and assuming a constant area of the grasper teeth between grasps and allowed the linear model to absorb the constant area.

RESULTS

The table of classification results for each tissue type is included in Table 1. This classification was taken at 176ms which corresponds to the average time a grasp takes to reach the force threshold corresponding to the center of the force range used in segmentations. Classification for a given grasp was considered correct if the minimum cumulative model error corresponded to the true class at the 176ms time.

	Actual			
vs	Kidney	Pancreas	Kidney Adipose	Pancreatic Adipose
Kidney	-	100%	95%	100%
Pancreas	100%	-	86%	60%
Kidney Adipose	78%	100%	-	100%
Pancreatic Adipose	94%	45%	82%	-

Tab. 1 Ordinal classification accuracies using the leave-one-out, one vs. one scheme

The seperation between grasp data for pancreas and kidney tissue is shown in Figure 2. The separation suggests significant discriminating information for strain and its derivative.

The relative contribution of each term in Equation 2 is represented in Figure 3 as a stack plot.

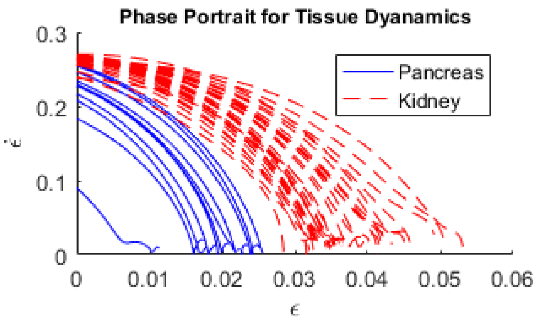

Fig. 2 Phase portrait of ϵ vs. $\dot{\epsilon}$ for pancreas and kidney tissue

DISCUSSION

The results indicate that tissue classification is possible with existing da Vinci® surgical graspers on cadaveric tissue. Previous work was limited to tissue classification using highly-customized surgical graspers [1] and on porcine tissue [3]. This work extends the previous work to classification of two different human cadaveric tissues and corresponding adipose tissue using a more common da Vinci® tool. For both kidney and pancreas, classification accuracies were 100%. Classification was achieved within 170ms of the start of the grasp which is below typical visual reaction time. Figure 3 indicates that dynamic and nonlinear terms have non-negligible contributions to the tissue model. Since all data were collected from sensors on the proximal end of the tool, this work can, in principle, readily integrate to a clinical setting. Placing sensors on the distal grasping end would have resulted in cleaner data, but it would be difficult to incorporate in a clinical setting due to sterilization issues, increased cost, and FDA approval requirements. Further work includes extending classification to more diverse tissue samples and testing a real-time version of the classification algorithm on the embedded hardware. Real-time application of this tissue classification in a surgical setting could help limit accidental tissue crushing and give direct information to the surgeon of the tissue being manipulated.

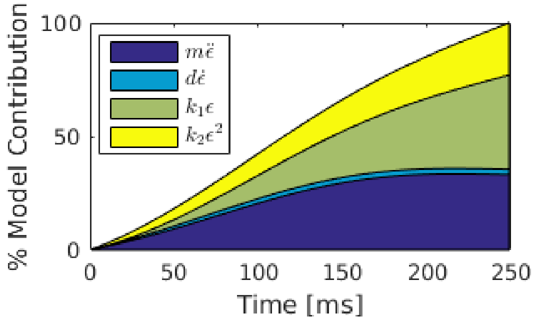

Fig. 3 Representitive stack plot showing the relative contribution for each term in the tissue model.

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