Tool Gravity Compensation and Deflection Characterization for the Galen Micro-Surgical System

Computer Integrated Surgery II

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Adam Polevoy and Parth Singh, under the auspices of Dr. Mahya Shahbazi and Dr. Russel Taylor

1. Introduction

- The Galen is a general purpose, hand-over-hand, admittance control robot developed mainly for otolaryngology.
- The Galen uses admittance control, where it measures the force a surgeon exerts on a tool and moves the tool proportionally.
- The Galen actively being developed and commercialized by the Galen Robotics company and is the subject of many research studies in the LCSR.
- Our goals during this project included
  - Developing and integrating gravity compensation functions for static and dynamic cases.
  - Characterizing deflection of the robot end effector.

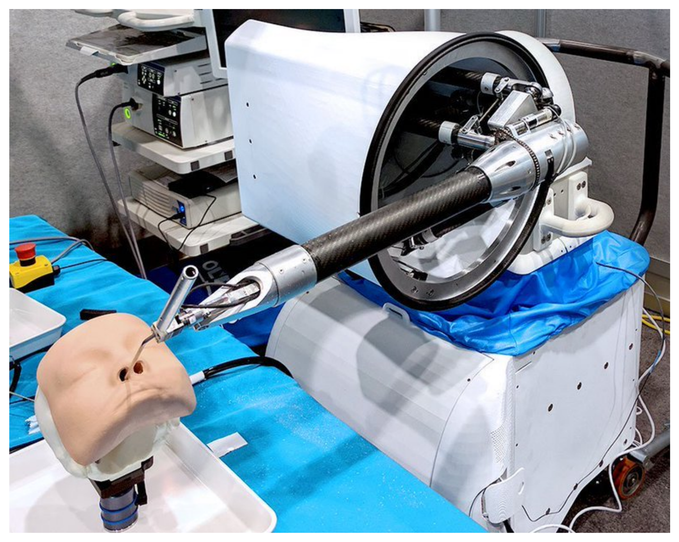

Fig. 1. Galen Mark 1 Surgical Robot

2. The Problem

- **Gravity Compensation**
  - The Robot's force sensor has no way of distinguishing between the forces exerted by the surgeon and those exerted by the tool itself.
  - This can result in unwanted motion that would be detrimental during surgery.
  - The current solution to allow the surgeons to manually remove the current recorded tool weight from the sensor readings.
  - As soon as a tool is moved to a different orientation, the problem reappears.
- **Deflection Characterization**
  - Due to flexibility in the robot's material and structure, there is a discrepancy between the calculated position of the robot and the true position.
  - This is a problem for automated tasks and virtual fixtures, as the robot may move into areas that can cause damage to the patient.

3. The Solution

Gravity Compensation

- Gravity compensation depends on the weight and the center of mass (CoM) of each tool.
- There is an additional weight and CoM due to the tool adaptor, referred to as the bias, that must be calculated.
- These parameters can be regressed by moving the end effector to a variety of positions and collecting the force sensor readings.
- The following equations are then used:

$$A_1 = \begin{bmatrix} R_{ts}(\vec{\theta}^{(1)})^T - R_{ts}(\vec{0})^T \\ \cdots \\ R_{ts}(\vec{\theta}^{(56)})^T - R_{ts}(\vec{0})^T \end{bmatrix}, \quad Y_1 = \begin{bmatrix} f_s^{(1)} \\ \cdots \\ f_s^{(56)} \end{bmatrix}$$

$$f_b = (A_1^T A_1)^{-1} A_1^T Y_1$$

$$A_2 = \begin{bmatrix} (R_{ts}(\vec{\theta}^{(1)})^T - R_{ts}(\vec{0})^T)\hat{f}_b(-R_{ts}(\vec{\theta}^{(1)})) \\ \cdots \\ (R_{ts}(\vec{\theta}^{(56)})^T - R_{ts}(\vec{0})^T)\hat{f}_b(-R_{ts}(\vec{\theta}^{(56)})) \end{bmatrix}, \quad Y_2 = \begin{bmatrix} \tau_s^{(1)} \\ \cdots \\ \tau_s^{(56)} \end{bmatrix}$$

$$p_{sb} = (A_2^T A_2)^{-1} A_2^T Y_2$$

Fig. 2. Equations for bias weight and CoM Regression

$$A_3 = \begin{bmatrix} R_{ts}(\vec{\theta}^{(1)})^T \\ \cdots \\ R_{ts}(\vec{\theta}^{(56)})^T \end{bmatrix}, \quad Y_3 = \begin{bmatrix} f_s^{(1)} - (R_{ts}(\vec{\theta}^{(1)})^T - R_{ts}(\vec{0})^T) f_b \\ \cdots \\ f_s^{(56)} - (R_{ts}(\vec{\theta}^{(56)})^T - R_{ts}(\vec{0})^T) f_b \end{bmatrix}$$

$$f_t = (A_3^T A_3)^{-1} A_3^T Y_3$$

$$A_4 = \begin{bmatrix} -R_{ts}(\vec{\theta}^{(1)})^T \hat{f}_t R_{ts}(\vec{\theta}^{(1)}) \\ \cdots \\ -R_{ts}(\vec{\theta}^{(56)})^T \hat{f}_t R_{ts}(\vec{\theta}^{(56)}) \end{bmatrix}, \quad Y_4 = \begin{bmatrix} \tau_s^{(1)} - (R_{ts}(\vec{\theta}^{(1)})^T - R_{ts}(\vec{0})^T)\hat{f}_b(-R_{ts}(\vec{\theta}^{(1)}))p_{sb} \\ \cdots \\ \tau_s^{(56)} - (R_{ts}(\vec{\theta}^{(56)})^T - R_{ts}(\vec{0})^T)\hat{f}_b(-R_{ts}(\vec{\theta}^{(56)}))p_{sb} \end{bmatrix}$$

$$p_{st} = (A_4^T A_4)^{-1} A_4^T Y_4$$

Fig. 3. Equations for tool weight and CoM Regression

- The force and torque readings of the tool at an orientation can then be predicted by following equations:
- The predicted forces can then be removed from the read values

$$g(\vec{\theta}^{(i)}) = (R(\vec{\theta}^{(i)}), p)$$

$$Ad_{g(\vec{\theta}^{(i)})} = \begin{bmatrix} R(\vec{\theta}^{(i)}) & \hat{p}R(\vec{\theta}^{(i)}) \\ 0_{3x3} & R(\vec{\theta}^{(i)}) \end{bmatrix}$$

$$F_{s,prediction} = Ad^T_{g_{ts}(\vec{\theta}^{(i)})} F_t + Ad^T_{g_{bs}(\vec{\theta}^{(i)})} F_b - Ad^T_{g_{bs}(\vec{0})} F_b$$

$$F_{s,compensated} = F_{s,uncompensated} - F_{s,prediction}$$

Fig. 4. Equations for Gravity Compensation

Deflection Characterization

- In order to calculate the true position of the robot we use an optical tracker, a tracker tool attached to the end effector, and a fiducial tracker attached to the robot body.
- We assume that the robot position is initially correct and calculate the Frame transformation between the base and the fiducial.
- We then use that to calculate the true position of the tool
- We moved to several different positions, collecting the expected position, the true position, the joint values, and the force sensor readings.
- We then trained a neural network to calculate the true position.

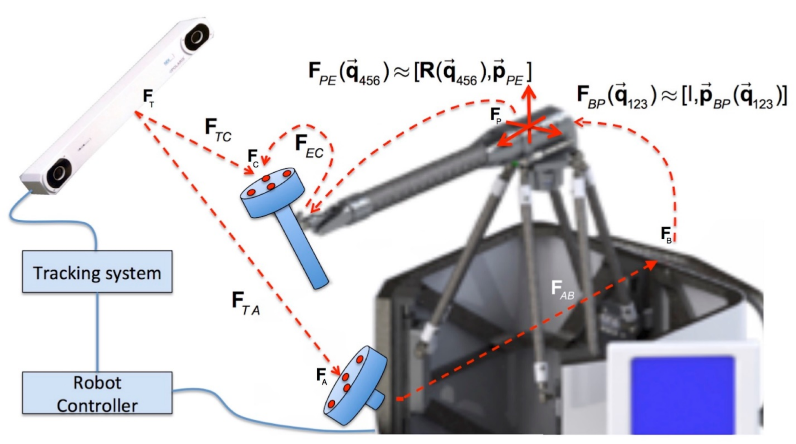

Fig. 5 The various robot frames required to calculate deflection

4. Outcomes and Results

Gravity Compensation

- Gravity compensation was successfully integrated into both existing versions of the robot.
- Our model resulted in a near zero compensated value at any arbitrary position.
- Additionally, an automated system for tool weight and center of mass regression was integrated.

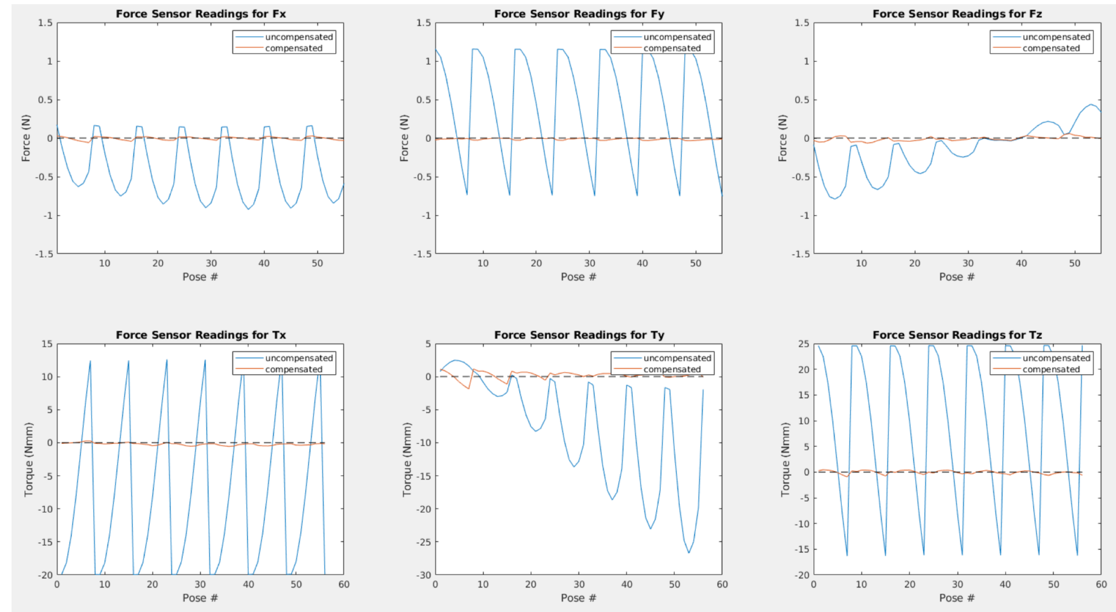

Fig. 6. Compensated vs uncompensated force values at varying positions

Deflection Characterization

- We successfully collected 8 data sets for model training
- We found that the robot suffered from a hysteresis issue where it did not move back to its original position after a large force had been applied.
- We trained an Long Short-Term Memory Recurrent Neural Network, the configuration of which can be seen below.
- Our model was not capable of predicting this hysteresis issue.
- The training error was as low as 9.483 mm. One example set is shown in Figure 8

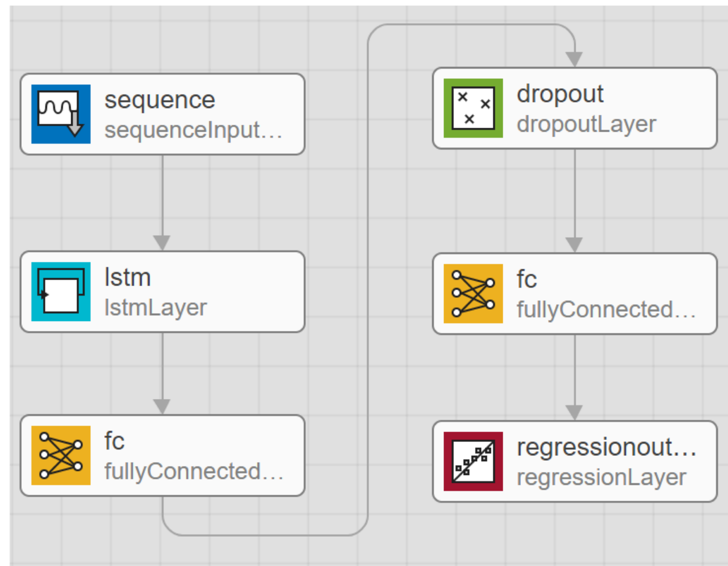

Fig. 7 Neural network structure

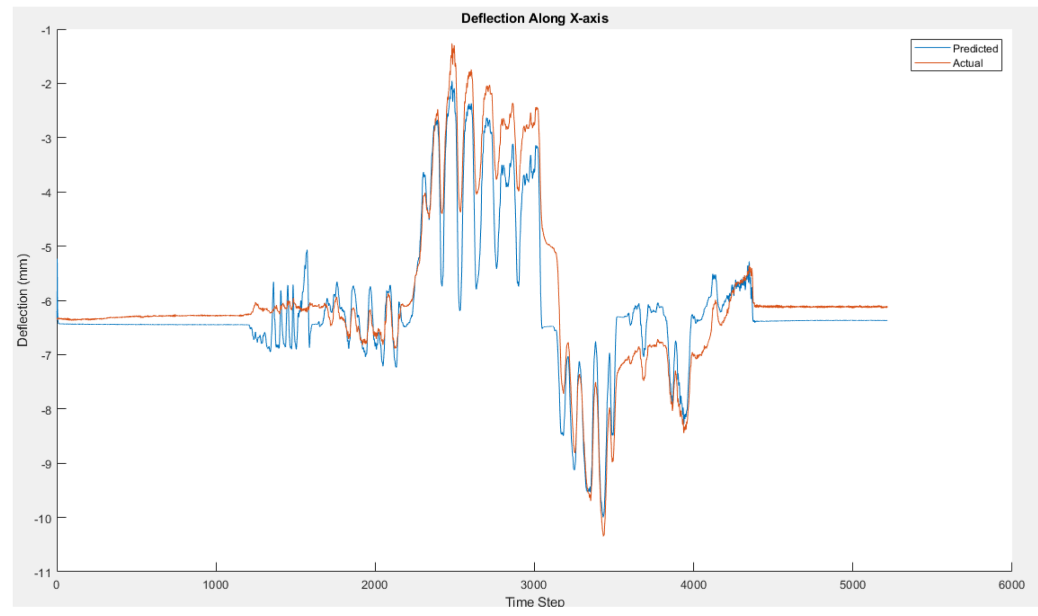

Fig. 8 Predicted vs true values of RNN, depicts hysteresis

5. Future Work

- Further work needs to be done to fully characterize deflection, including additional data collection and attempting additional model parameters.
- Gravity compensation for tools with cable drag and moving parts will need to be implemented.

6. Lessons Learned

- We learned how to quickly trace through code to find workflows and values, along with the importance of documentation.
- We learned the importance of analyzing training data before developing models, as we found that some of data sets for deflection characterization were missing parts of their sequences.

7. Work Distribution

- Adam lead data analysis, model development, and worked on model integration.
- Parth wrote data collection code, worked on model integration, and developed the machine learning models.

8. Acknowledgement

- Special thanks to the Galen employees, along with Dr. Shahbazi and Dr. Taylor for their support and mentorship.

9. References

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