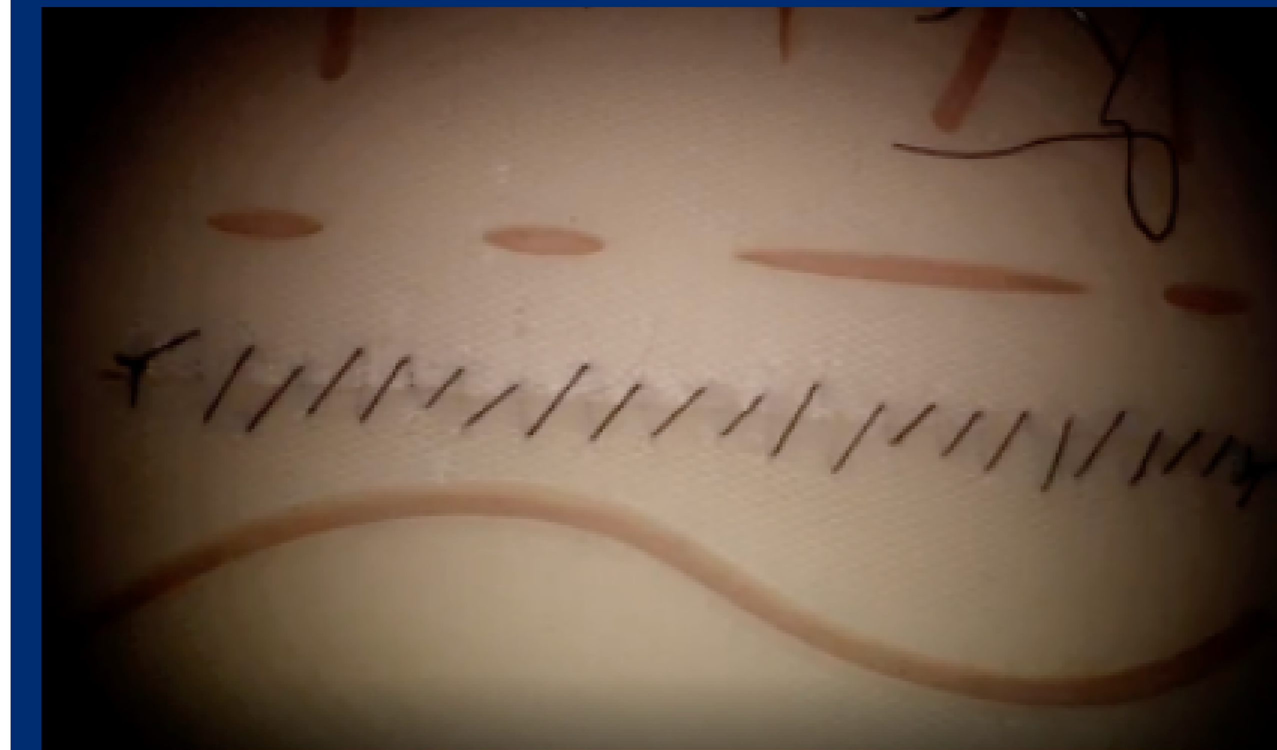

Autonomous Wound Closure

Machine learning model to autonomously perform surgical wound closure

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Introduction

Clinical Background
Suturing is a necessary, yet tedious task involved in 300 million surgeries per year. Wound closure is a time-consuming operation in which duration correlates with complication risk. To provide an example, the hour-long knee arthroplasty procedure can require up to 30 minutes of wound closure.

Machine Learning Potential
Suturing is composed of 4 standardized tasks, which have the potential to be automated with surgical robotics: needle pick-up, needle handover, needle throw, and knot-tying.

Significance

Our goal is to develope a machine learning model to autonomously perform surgical wound closure and improve data collection infrastructure with the dVRK SI for future imitation learning research.

Our autonomous wound closure framework has the potential to:

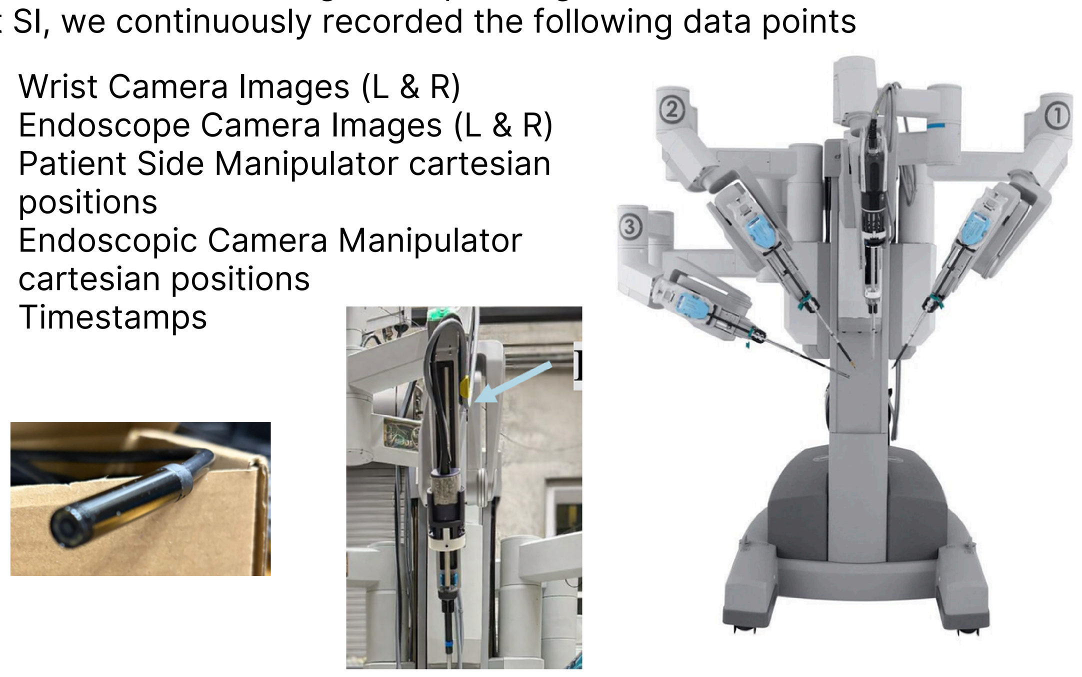
- Reduce wound closure variability and time
- Minimize surgeon time in operating room
- Improve quality and ease of dVRK data collection

Previous work in autonomous suturing has achieved some success on individual subtasks within suturing, but never full wound closure.

Materials and Methods

Data Collection: Through teleoperating the da Vinci Reasearch Kit SI, we continuously recorded the following data points

- Wrist Camera Images (L & R)
- Endoscope Camera Images (L & R)
- Patient Side Manipulator cartesian positions
- Endoscopic Camera Manipulator cartesian positions
- Timestamps

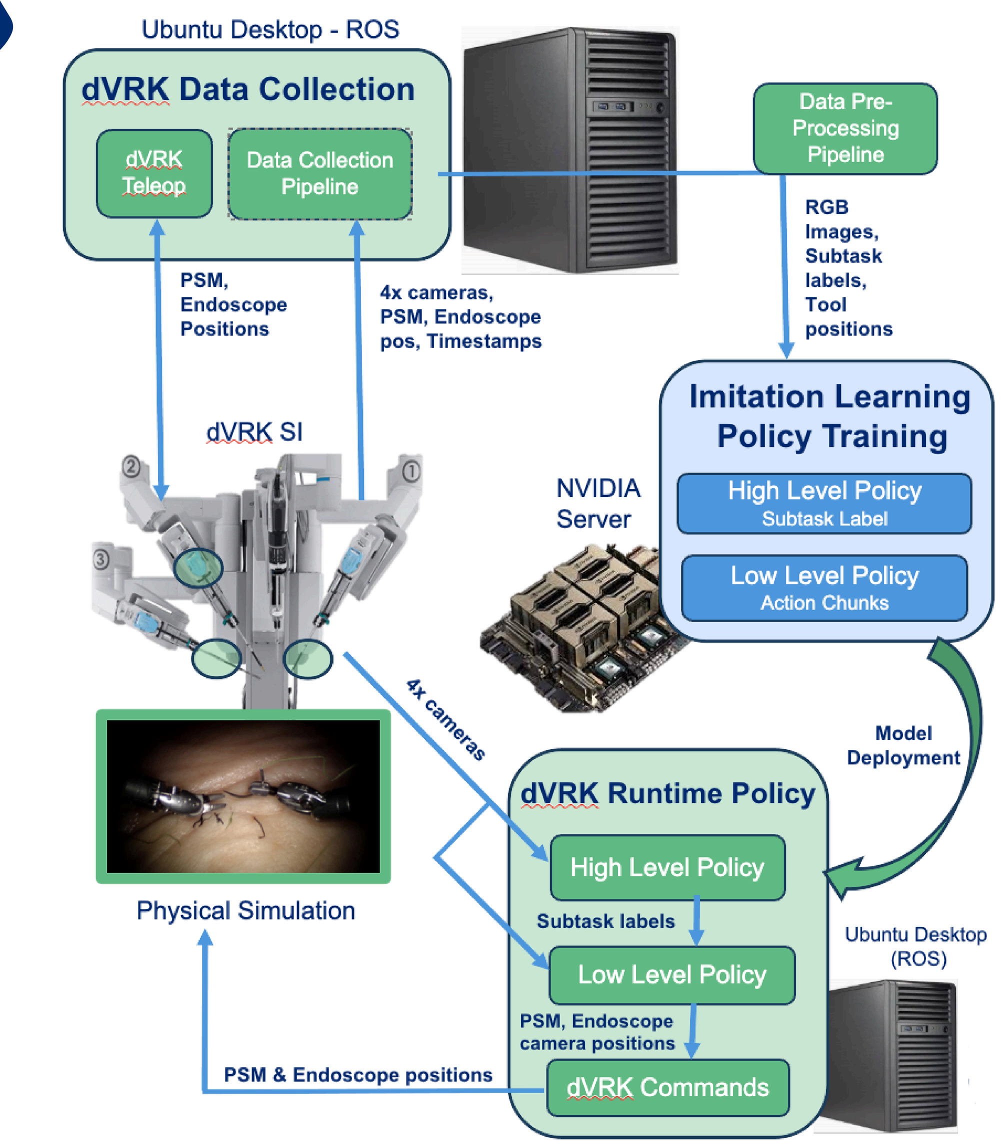


Process & Results

1

Current dVRK data collection and imitation learning research is limited by poor synchronizaiton of camera and kinematic data. Our pipeline adresses this with:

- **Updated dVRK Hardware**
  - Wrist Cameras: 15 ⟶ 30 Hz
  - Endoscope Cameras: 30 ⟶ 50 Hz
- **Updated recording & data processing infrastructure**
  - ROS1 ⟶ ROS2: improves synchronization of multi-modal data, lowers latency, and minimizes jitter
  - GStreamer Usage: directly incodes and saves camera data to mp4
  - Recording ROS topics in ROS bags: allows for more synchronized timestamps and corresponding kinematic and camera data
  - Frame Trimming: removes stale frames, increasing procedure speed and decreasing time spent extracting repeat data



2 Our Project Scope (shown in Green):

We collected an initial dataset with 7 hours of dVRK teleoperated data on varying wound lengths and suture pads

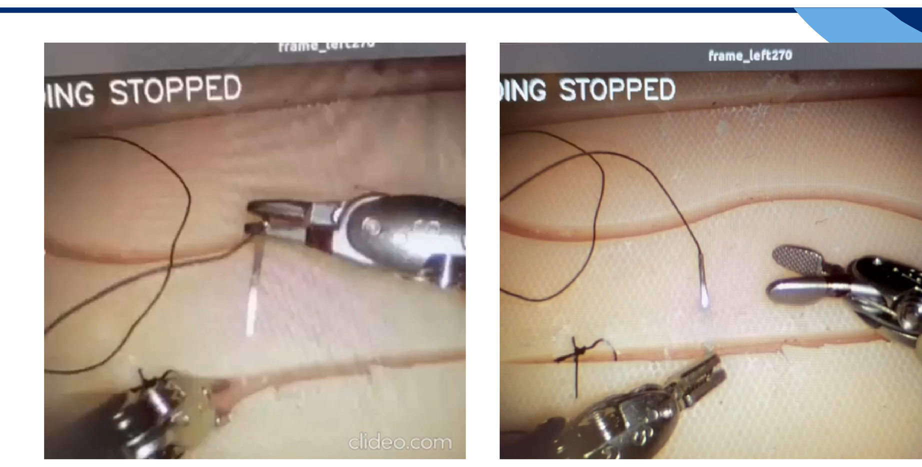
Unfortunately, the dVRK left master tool manipulator was damaged and we were unable to continue data collection

3 Training & Testing

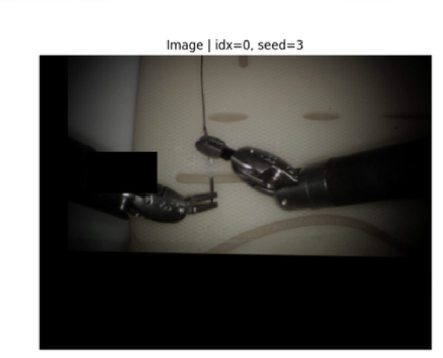
Initial Results: We found that our results for the needle puncturing and pull through subtasks were most successful on smaller, uniform wounds

We conducted 20,000 epochs of Action Chunking Transformer (ACT) training

Model Training Data Variation	Offline Evaluation MAE Metric
Trained on 3 and 5 cm wound datasets	0.05
Trained on 3, 5, 7 and 8 cm wound datasets	0.12
Trained on 4x 3 cm datasets only without knot tying	0.12



Model Training Data Variation	Needle Puncture	Needle Pull Through
3 and 5 cm wound datasets	1/5	0/5
3, 5, 7 and 8 cm wound datasets	1/5	1/5
4x 3 cm datasets without knot tying	2/5	3/5

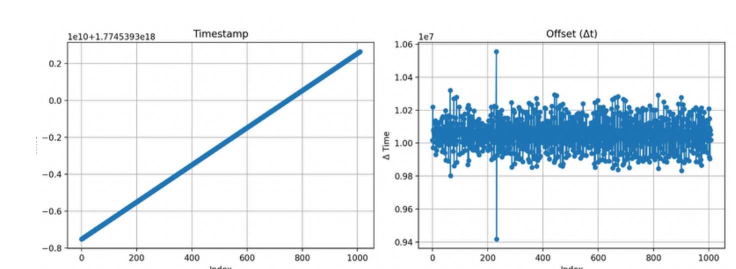


4 Recording Application Validation

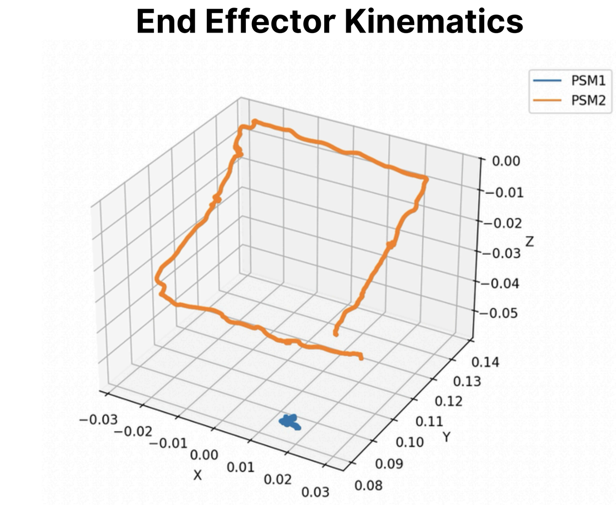
To test our recording application and hardware, we conducted the following tests:

- Linear timestamp increase and step size following sensor rate ✓
- Kinematics values of end-effector matches desired motion ✓
- Correlated camera data and kinematics within 10ms threshold ✓
- Correct number of recorded frames ✓
- Predicted and ground truth actions ✓

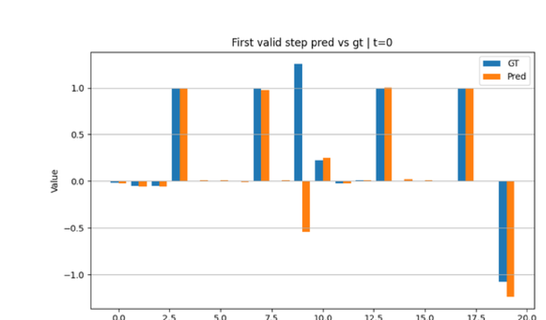
Timestamp and Sensor Offset Data



End Effector Kinematics



Predicted vs Actual Action Dimensions



Conclusion

By increasing the synchrony of camera, kinematics, and timestamp data, we were able to improve data collection infrastructure with the dVRK SI. While we were not able to collect enough data due to robot damage, we hope to train a model which can autonomously produce the full continuous baseball suture in the future.

QR code to our wiki page – JHU credentials required for sign in

Thank you to the IMERSE lab for allowing us to use the dVRK SI. Thank you to our professors and project mentors for your guidance!