Da Vinci Tool Torque Mapping over 50,000 Grasps and its Implications on Grip Force Estimation Accuracy

Nathan J. Kong, Trevor K. Stephens, and Timothy M. Kowalewski

***Abstract*—Despite the increasing use of the da Vinci surgical robot, clinicians often claim that the inclusion of force measurement at the grasper could enhance the use of these robots in surgery. Many methods have been proposed to accurately estimate this force using already-existing sensors on the da Vinci robot. However, a key weakness in these methods is that they rely on a training dataset which was likely obtained at the beginning of a tool's life, and does not accurately represent the state of the tool throughout use. This work aims to address this problem by assessing the grip force estimation error over the lifetime of a single da Vinci tool, and to propose a method to maintain this estimation error at less than 2 mNm. We found that the most significant changes in the tool were seen in the first 1,000 grasps. Despite these changes, our method to periodically retrain our algorithm maintained the error under 2 mNm. An accurate estimation error has implications in haptics as well as obtaining *in-vivo* tissue properties during surgical procedures.**

I. Background

The da Vinci surgical system has been widely adopted for many surgeries, particularly within urological procedures. In 2016 alone, approximately 753,000 surgical procedures were performed with the da Vinci Surgical System, which constitutes a 15% year-over-year growth [1]. The adoption has progressed to the point where performing radical prostatectomy procedures using the da Vinci robot is now considered the gold standard [2]. Despite the rapid adoption, many clinicians still state that there is a need for measuring force at the site of grasping during surgery for potential clinical applications such as haptics [3], [4].

Another potential benefit garnered from an accurate measurement of force at the grasping site is to deduce tissue properties of grasped organs. There is a clear lack of *in-vivo* tissue properties reported in literature [5], [6], and a possible solution is to capitalize on the rapidly increasing amount of surgeries performed robotically, where tissue grasping occurs frequently. This approach could potentially provide tissue properties which would encapsulate the variability across patients as well as disease states.

Regardless of the applied benefit of measuring forces at the tool-tissue interface, the fact remains that current surgical robots are not equipped with a reliable measurement or estimate of this force. However, several research efforts have been recently conducted to ascertain this value. These efforts generally fall into two categories: direct measurement and indirect estimation.

The methods for direct measurement of tool-tissue forces require modifications to existing surgical tools by placing sensors at the grasping site. This is accomplished by various means, but each approach is complicated by sterilization issues and the high cost added to these disposable tools. Examples which fall in this category include miniature force sensors integrated into the grasper jaw [7], force sensors affixed externally to the tool jaws [8], and re-designs of the jaw and tool shaft to accommodate additional sensors [9].

Indirect measurements do not suffer from sterilization or cost issues like the aforementioned direct measurements because they rely on sensors that do not come in contact with the patient. These sensors are already inherent in the current surgical robot setup, and therefore would not require additional costs. Since these sensors are not placed physically at the grasping site, the sensor measurements must be used in conjunction with an estimation technique to yield forces at the tool-tissue interface. One such method is proposed in [10], which utilizes Gaussian Process Regression to estimate these forces.

Although these estimates are known to be less accurate than the direct measurement approach, they are much more feasible since they do not require hardware modifications. The success of these techniques have been verified in laboratory settings, but there are still some weaknesses that need to be addressed. A main weakness is their reliance on a training dataset, which is generally taken at the beginning of operation and used throughout the estimation. With continual use of the tool, it is likely that the cable-pulley mechanisms inside da Vinci tools will begin to wear down, and result in greater estimation errors. This work focuses on overcoming this gap. The objective of this research is to characterize the grip force estimation error over an extended lifetime (50,000 grasps) of a single da Vinci EndoWrist surgical tool, and if necessary, propose and test a method to maintain an average estimation error of less than 2 mNm, which is comparable to previous estimation errors on surgical tools [10]. This research is applicable to the several

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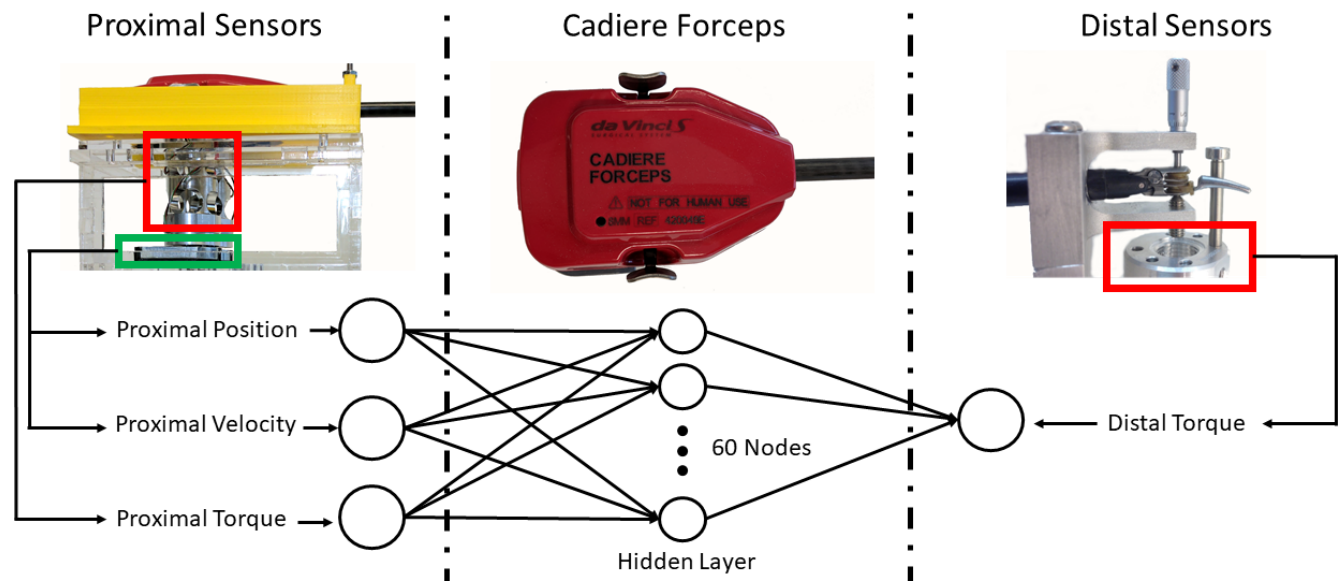

Figure 1: Experimental setup with proximal sensors used as input to the neural network (left), Cadiere Forceps da Vinci tool cable-pulley system modeled with hidden layer of the neural network (center), and distal sensors used as output to the neural network (right)

estimation methods for predicting grip force at the tool-tissue interface which rely on a trained model of the tool, but fail to include the potential model changes as the tool wears down. In this work we chose to employ a neural network as our estimation technique, which is an estimation technique that relies on a training dataset beforehand. As part of this work we also present the raw data collected which depicts the torque mapping of the tool as a function of spindle angle over the 50,000 grasps.

II. Methods

A. Data Collection

The grasping data were collected for a total of 50,000 grasps to simulate approximate wear in a typical life of a tool. Grasps were conducted in increments of 1,000, which is called a "grasping epoch". A total of 50 grasping epochs were conducted to form the 50,000 total grasps. For analysis purposes, these grasping epochs were divided into smaller increments of 100 grasps which we called "grasping sub-epochs". The grasping epochs are used in the analysis of general trends over the lifetime of the tool, whereas the sub-epochs are used to further investigate these trends over a more specific window of time.

All 50,000 grasps were performed with a 0.5 Hz sinusoidal trajectory in position with a resistive torque of approximately 145 mNm opposing the jaw motion. All grasps were performed on a single jaw of da Vinci Cadiere Forceps ranging from fully open ($-60°$) to fully closed ($0°$). The grasping was performed via actuation of the da Vinci EndoWrist spindles at the proximal end with custom hardware as depicted in Figure 1. The resistive torque on the distal end was applied via a motor as described in [11]. Measurements of torque and position were collected at both the proximal and distal ends, and were time-synchronized.

B. Torque Mapping Calculation

To assess the quality of a tool over its lifetime, the proximal-to-distal torque mapping of the tool was calculated at each epoch and compared across all epochs. The torque mapping at the ith epoch, ${}^{i}M(\theta)$, is defined as the ratio between proximal and distal torques, as shown in Eq. 1, and is computed as a function of the proximal-side spindle angle, θ.

$$ {}^{i}M(\theta) = \frac{{}^{i}T(\theta)_{d,avg}}{{}^{i}T(\theta)_{p,avg}} \qquad i = 1, 2, ..., 50 \tag{1} $$

Here,

${}^{i}M(\theta)$	is torque mapping of the ith epoch
${}^{i}T(\theta)_{d,avg}$	is average distal-end torque of the ith epoch
${}^{i}T(\theta)_{p,avg}$	is average proximal-end torque of the ith epoch

The average proximal and distal end torques were computed by binning each grasp within an epoch into position bins, and averaging across the binned data.

C. Neural Network Estimation

The time-synced position and torque measurements from proximal and distal ends were used to train a neural network to estimate grip force as depicted in Figure 1. This estimate of grip force is therefore an estimate at the distal end based on proximal-end sensing alone. The inputs to the neural network are proximal-end position, velocity, and torque, and the output is distal-end torque. The neural network architecture contains a single hidden layer with 60 nodes. All of the input and output features were normalized using min-max normalization

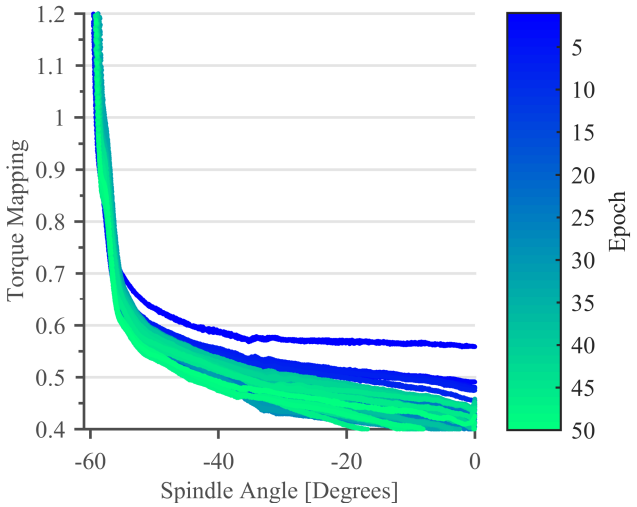

Figure 2: Torque mapping change over tool lifetime as a function of spindle angle as computed by Equation 1.

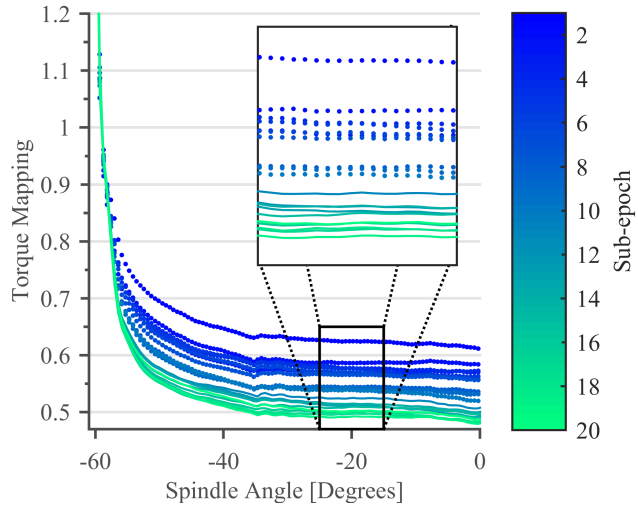

Figure 3: Torque mapping changes analyzed at a sub-epoch level for epochs 1 and 2. All 10 sub-epochs from epoch 1 are depicted by dots and all 10 sub-epochs from epoch 2 are depicted by lines.

as a pre-processing step. A log-sigmoid transfer function was used at the hidden layer, and a purely-linear transfer function was used at the output layer. The training method was scaled conjugate gradient backpropagation [12] as implemented in the Matlab Neural Network Toolbox (The MathWorks, Inc., Natick, Massachusetts). For all neural network trainings, 20% of the data were reserved for testing (i.e. not used in the training process) so as to not bias the training.

D. Estimation Accuracy

To measure the changes of the tool over its lifetime, a neural network was trained on data from the first grasping epoch data, and each successive grasping epoch was run through this neural network to obtain an estimate of the grip force at the jaw. The estimation error was recorded at each epoch and compared to the error from the first epoch. Additionally, a baseline comparison was conducted by retraining a neural network at each epoch to compute the baseline error for each individual epoch.

We propose a method to maintain the predetermined 2 mNm threshold of estimation error, which is employed whenever the estimation exceeds that error threshold. The method entails retraining the neural network at the epoch which exceeds the error threshold, and to continue using this newly trained neural network until the error exceeds the threshold again. In this way the error estimate will reduce back down to the baseline measurement for each of these "retraining epochs". From there, the estimation may grow again until the exceeded threshold triggers the next retraining epoch.

III. Results

The torque mapping was computed according to Equation 1 and is shown graphically in Figure 2 for all 50 epochs. Additionally, Figure 3 shows the analysis of epochs 1 and 2 at a sub-epoch level; each epoch consists of 10 sub-epochs. This sub-epoch analysis allows for a more detailed look at the data within specific epochs.

The estimation errors from the baseline case (i.e. retraining a neural network at each epoch) is shown in Figure 4. The plot shows a boxplot of the estimation error for all points within the testing dataset. Inset A depicts the results from epoch 1 (original epoch) when analyzing it at a sub-epoch level. Similarly, inset B depicts the results from epoch 50 (final epoch) when analyzing it at a sub-epoch level. Note that when analyzing the data at a sub-epoch level, the neural net was trained on data from the first sub-epoch and successive sub-epoch data were run through this neural net.

The estimation error with retraining applied is shown in Figure 6. The retraining intervals are marked with vertical dashed lines, and occurred at epochs 2, 6, 26, and 47 as determined by instances when the error exceeded the 2 mNm threshold. At these retraining intervals the estimation error is equivalent to the corresponding epoch in Figure 4.

Figure 7 depicts the data from Figures 4-6 on the same axes for comparison. Instead of depicting the data as boxplots, the average estimation error across the entire epoch was plotted for each epoch for the three cases: trained against its own epoch, trained against the original epoch, and trained against the most recent retraining epoch. Once again, the vertical dashed lines are included to highlight retraining intervals.

IV. Discussion

The data from Figure 2 suggests a noticeable difference in the torque mapping from epoch 1 to epoch 50. On further investigation at the sub-epoch level, it appears that most of the change happens within the first epoch as the variability is much greater for the sub-epochs of epoch 1 than with the sub-epochs

in epoch 2 (Figure 3). This trend continues with each successive epoch, as the highest variability in torque mapping was witnessed in epoch 1. This suggests that approximately 1,000 grasps are needed to precondition the tool to eliminate the large variations. The general trend for this torque mapping is decreasing, which implies that brand new surgical tools require less input torque to achieve a specific output torque compared with older tools. This is likely attributed to components such as bearings wearing down and creating more friction in the system. Once the tool is worn down, the torque mapping tends toward a steady-state value.

The baseline estimation error is fairly low (approximately 1 mNm average) for each epoch as depicted in Figures 4 and 7. Once again, further investigation reveals that although the errors are low, there is much more variability and slightly higher estimation error for earlier epochs (e.g. epochs 1 and 2) than for later epochs (e.g. epochs 3-50). This agrees with the torque mapping results we observed, as the neural net estimation is suffering due to the variability within an epoch when the tool is brand new and is still variable. This is further seen from inset A and inset B within Figure 4, as inset A depicts a steep increasing estimation error for epoch 1 when

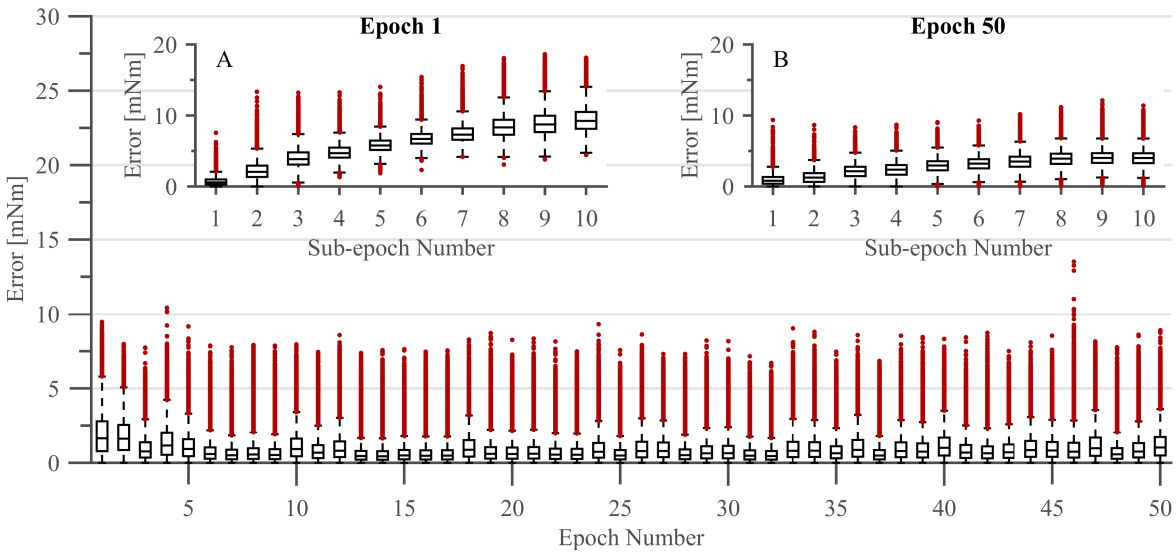

Figure 4: Baseline comparison depicting each epoch's estimation error when put through a neural network trained on data from its own epoch. Inset A shows data from epoch 1 (original epoch) analyzed at a sub-epoch level. Inset B shows data from epoch 50 (final epoch) analyzed at a sub-epoch level.

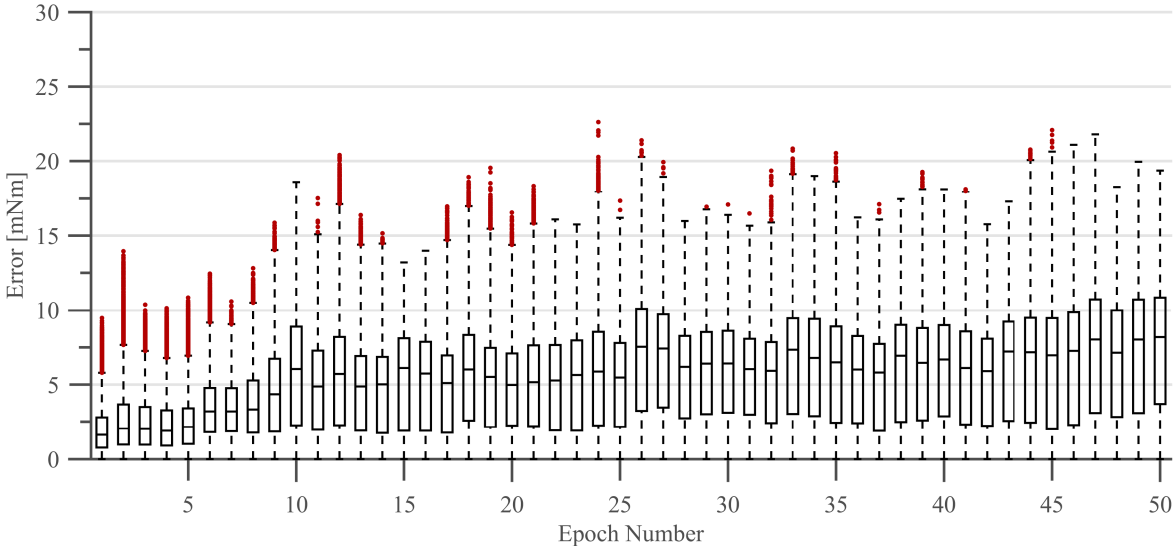

Figure 5: Each epoch's estimation error when put through a neural network trained on data from epoch 1

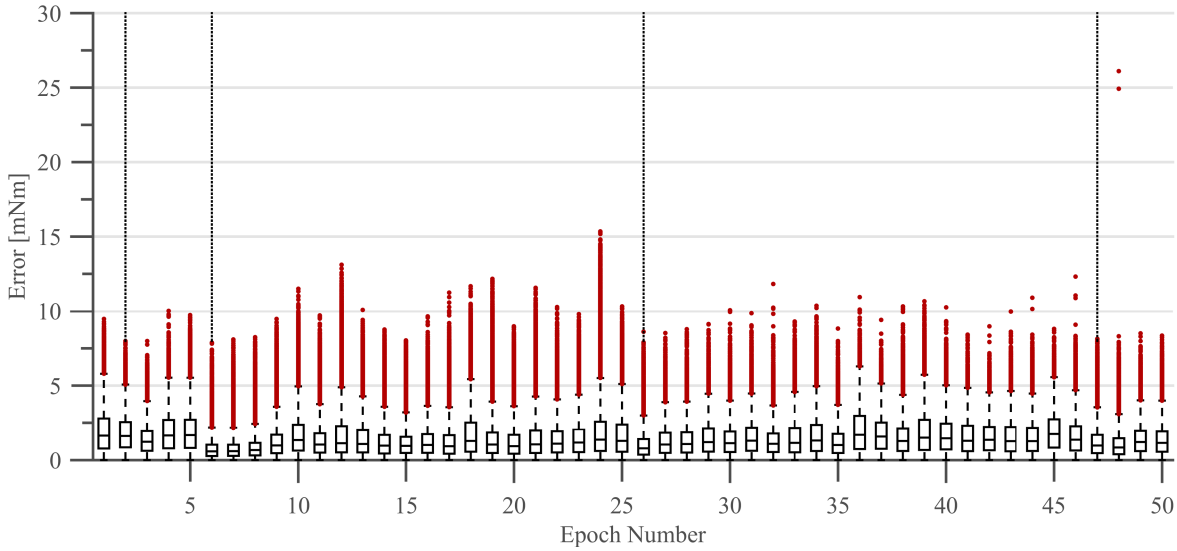

Figure 6: Each epoch's estimation error when put through a neural network trained on data from the most recent retraining epoch. The retraining epochs are located at epochs 2, 6, 26, and 47 and are marked with a vertical dashed line.

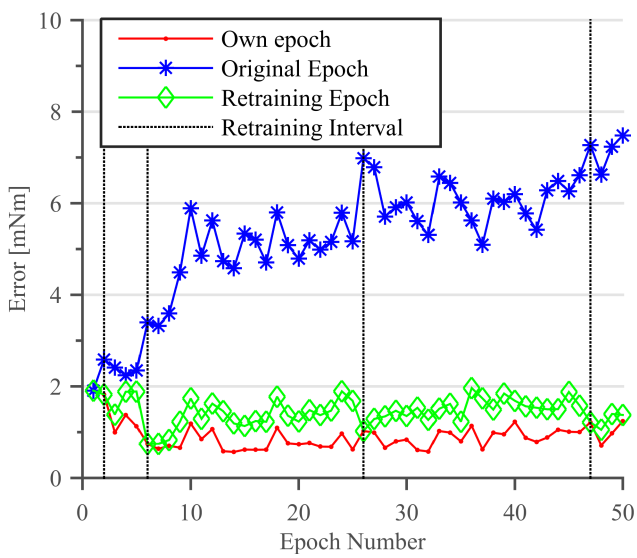

Figure 7: A summarizing graph depicting average estimation error per epoch for three cases: training on its own epoch (red), training on the original epoch (blue), and training on the most recent retraining epoch (green). For clarity, the determined retraining intervals are marked with a vertical dashed line.

analyzed at a sub-epoch level, and inset B depicts a more mild estimation error for epoch 50 when analyzed at a sub-epoch level. This further suggests that tool changes occur mainly within the first 1,000 grasps of a tool.

The results in Figure 5 show that estimation error suffers when only relying on a training dataset from the original epoch. As verified in Figure 7, there is approximately a five-fold increase in average error starting from about the 10th epoch until the end of testing. This error is significant, but remains fairly constant after the 10th epoch, which suggests that the tool is reaching a fairly consistent physical state and therefore a retraining method is feasible to reduce this error.

The results when applying the method for error reduction are shown in Figure 6. Based on the 2 mNm threshold, this data suggests having retraining epochs after epoch 2, 6, 26, and 47. However, the estimation error is more severe in earlier epochs suggesting that the retraining at epochs 2 and 6 are much more necessary than the retraining epochs at epochs 26 and 47. Figure 7 depicts the average estimation error when employing this retraining method, and it is shown that less than 2 mNm estimation error is maintained across all epochs. This retraining method is feasible within the workflow of surgery, but is not ideal. Since the most significant amount of changes occur within the first 1,000 grasps, the more practical solution may be to precondition tools with a routine grasping protocol before deploying the tool on-line.

Another feasible implementation of this retraining method is for cases when tools are to be used specifically for collecting in-vivo tissue properties. This work suggests that it would be more ideal to collect these tissue properties on preconditioned tools, and to ideally collect training data to train an estimation technique as close as possible prior to collecting the data. In this sense, a more accurate estimate of grip force could be ascertained.

This research provides new knowledge concerning the impact of estimation error over the lifetime of surgical tools, yet future questions remain. The first area we plan to explore is the impact of lubrication. Clinicians often disregard the recommendation to use lubrication when using the da Vinci tools, and the potential implications of lubrication on estimation error remain unclear. We hypothesize that using lubricant at the

jaws throughout the lifetime of the tool will have negligible effect on estimation error of grip force, as the cable-pulley mechanism will deteriorate despite the use of lubrication. This is worth investigating, as it is currently a recommendation mostly disregarded by clinicians. Other future work includes conducting this study on a wider tool population to verify the results herein.

This work successfully characterized the grip force estimation error over the lifetime of a da Vinci surgical tool. Additionally, a method was presented which maintained a 2 mNm estimation error. The torque mapping of the tool as a function of spindle angle was also compared over the tool's lifetime. This work is applicable to grip force estimation techniques which require training datasets. The implications extend to force-feedback in surgery for possible applications in haptics or tissue property estimation. From this work we conclude that the mechanical properties of da Vinci tools significantly change over time, with much of that change occurring over the first 1,000 grasps. We also report that this directly impacts the estimation accuracy which can be overcome with our proposed retraining method, or mitigated by using preconditioned tools.

References

[1] "Annual report 2016," Intuitive Surgical, Inc., Tech. Rep., 2016. [Online]. Available: http://www.annualreports.com/HostedData/AnnualReports/PDF/NASDAQ_ISRG_2016.pdf

[2] S. Chopra, A. Srivastava, and A. Tewari, "Robotic radical prostatectomy: The new gold standard," *Arab journal of urology*, vol. 10, no. 1, pp. 23–31, 2012.

[3] M. Tavakoli, *Haptics for teleoperated surgical robotic systems*. World Scientific, 2008, vol. 1.

[4] E. U. Braun, H. Mayer, A. Knoll, R. Lange, and R. Bauernschmitt, "The must-have in robotic heart surgery: haptic feedback," in *Medical robotics*. InTech, 2008.

[5] C. Basdogan, S. De, J. Kim, M. Muniyandi, H. Kim, and M. A. Srinivasan, "Haptics in minimally invasive surgical simulation and training," *IEEE computer graphics and applications*, vol. 24, no. 2, pp. 56–64, 2004.

[6] M. Sedef, E. Samur, and C. Basdogan, "Real-time finite-element simulation of linear viscoelastic tissue behavior based on experimental data," *IEEE Computer Graphics and Applications*, vol. 26, no. 6, 2006.

[7] U. Kim, D.-H. Lee, W. J. Yoon, B. Hannaford, and H. R. Choi, "Force sensor integrated surgical forceps for minimally invasive robotic surgery," *IEEE Transactions on Robotics*, vol. 31, no. 5, pp. 1214–1224, 2015.

[8] C.-H. King, M. O. Culjat, M. L. Franco, J. W. Bisley, G. P. Carman, E. P. Dutson, and W. S. Grundfest, "A multielement tactile feedback system for robot-assisted minimally invasive surgery," *IEEE Transactions on Haptics*, vol. 2, no. 1, pp. 52–56, 2009.

[9] G. Tholey and J. P. Desai, "A modular, automated laparoscopic grasper with three-dimensional force measurement capability," in *Robotics and Automation, 2007 IEEE International Conference on*. IEEE, 2007, pp. 250–255.

[10] Y. Li and B. Hannaford, "Gaussian process regression for sensorless grip force estimation of cable-driven elongated surgical instruments," *IEEE Robotics and Automation Letters*, vol. 2, no. 3, pp. 1312–1319, 2017.

[11] N. J. Kong, T. K. Stephens, J. J. O'Neill, and T. M. Kowalewski, "Design of a portable dynamic calibration instrument for da vinci si tools," *ASME. Frontiers in Biomedical Devices, 2017 Design of Medical Devices Conference*, 2017.

[12] M. F. Møller, "A scaled conjugate gradient algorithm for fast supervised learning," *Neural networks*, vol. 6, no. 4, pp. 525–533, 1993.