Impact of Jaw Orientation on Grip Force Estimation for a da Vinci EndoWrist Surgical Tool

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INTRODUCTION

The utlization of accurate grip force estimates during surgical procedures has been widely proposed as a benefit for robotic surgery. Several research publications have proposed varying methods for obtaining this estimate with generally high accuracy [1, 2]. Despite these positive results, many of the proposed methods neglect the impact that the jaw orientation (i.e. roll, pitch, and yaw) has on estimation accuracy. Previous work has shown that grip force in general varies up to three-fold with jaw orientation [3]; we aim to extend upon these raw results by quantifying how accurate our proposed grip force estimation technique is across a wide range of jaw orientations. This work is a further step towards establishing more realistic expectations for applications of grip force estimation in a surgical setting.

MATERIALS AND METHODS

Custom hardware was built and utilized to obtain synchronized data between the distal end (Fig. 1A) and proximal end (Fig. 1B) of a da Vinci EndoWrist Maryland Bipolar Forceps during sinusoidal grasping. Position and torque data were time-synchronously collected on both ends. Details of the hardware setup including the sensors used on the proximal and distal ends are explained in [4] and [5], respectively. For this dataset, the tested range of orientations included the following: pitch angles (-60 to +60°), roll angles (-90 to +90°) and yaw angles (-90 to +30°). The jaw position (θ) is actuated by the same degree of freedom as yaw. For testing, this jaw position performed grasps 45° from the current yaw angle in a sinusoidal trajectory. Resistive torque was applied directly to the distal jaw at a fixed point and ranged from 25 to 100 mNm.

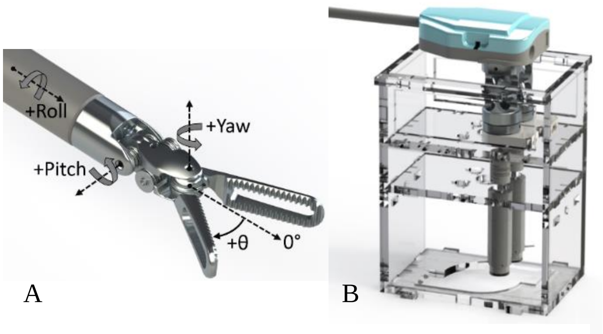

Fig. 1 Renderings of (A) distal-side with coordinate frame notation (B) proximal-side hardware for data collection

The estimation technique utilized in this work is an artificial neural network similar to the one explained in [4]. The neural network architecture consisted of 60 nodes in a single hidden layer, with input features of position, velocity, torque, pitch spindle, and roll spindle all measured on the proximal end. The neural network was trained with torque as the output as measured at the distal end. Training was performed using the scaled conjugate gradient method for back-propagation with a log-sigmoid activation function at the hidden layer and a purely linear activation function at the output layer. The neural network was implemented using the Neural Network Toolbox in MATLAB.

Two separate experiments were conducted. Experiment 1 consisted of fixing pitch and varying the roll and yaw angles; experiment 2 consisted of fixing roll and varying the pitch and yaw angles. For experiment 2, the variations on pitch limited the yaw angles we could test due to physical constraints of the hardware. Therefore, for this experiment a subset of yaws were used from 0 to +30°. A control dataset was used for comparison which consisted of fixing all three degrees of freedom (i.e. fixing roll, pitch, and yaw). In this manner a more diverse (and realistic) subset of jaw orientations were included for experiments 1 and 2 as opposed to traditional approaches of testing in the jaw's neutral orientation (i.e. fixing all three degrees of freedom). For each experiment the respective dataset was binned into five randomized test subsets with the complementary data utilized for training data. This resulted in five different training datasets, and accordingly five-fold cross validation was performed.

The average root-mean-square error (RMSE) and 95th percentile across all five folds was computed for both experiments and the control. Additionally a time series was plotted to visualize the estimation errors in the temporal domain.

RESULTS

The results for RMSE, 95th percentile, as well as number of time samples (N) across all folds for both experiments and the control are included in Table 1.

A sample time series is shown in Figure 3 to give visual context of the estimation in the temporal domain. The time-series is shown in a non-neutral jaw orientation for experiments 1 and 2, and the neutral jaw position for the control.

Tab. 1 Results from each dataset depicting averages from the five-fold validation for RMSE and 95th percentile as well as the number of time samples in the respective dataset.

Dataset	RMSE [mNm]	95th % [mNm]	N [samples]
Control (Varied no DOF)	1.37	3.97	30,691
Experiment 1 (Varied roll, yaw)	2.85	5.22	764,076
Experiment 2 (Varied pitch, yaw)	2.94	4.98	305,681

DISCUSSION

The results from experiments 1 and 2 show that orientations in these datasets. The RMSE for both experiments increases when compared with the control, but is still relatively low at 2.90 mNm, on average.

This estimation technique compares favorably to existing grip force estimation results reported in literature, even with the non-fixed jaw orientations. As an example, the results in [1] report an average error of 0.07 N for grasps with a peak force of roughly 1 N. This was accomplished via Gaussian Process Regression. Our results, when converted to force, resulted in an RMSE of 0.29 N for grasps with a peak force of approximately 10 N. When comparing the error percentage of peak grasping force the results in [1] yield 7% error, while our results yield 3% error. This comparison is not meant to definitively state which estimation techniques is superior, especially considering the multiple factors which differ between experimental setups. However, it is an attempt to suggest that despite the inclusion of varied jaw orientations, estimation of the force at the distal end is realizable.

This work progresses the efforts in grip force estimation by incorporating a wider range of jaw orientations in the training dataset. However, there are some shortcomings within this work which still exist as barriers to transition this work in clinical settings. These shortcomings are recognized and presented here as future work.

Firstly, the experimentation was accomplished by varying two degrees of freedom at a time while keeping one fixed. Although this may accurately represent some surgical scenarios (e.g. fixed roll with varied pitch and yaw), the more generalizable approach would be to allow all degrees of freedom to vary in the training dataset.

Secondly, the impact of grasping frequency was purposefully neglected in this study, but would need to be analyzed prior to clinical adoption. Although many surgical motions occur at relatively slow speeds, the existing estimation technique may suffer if training data across all these speeds is not included.

Additionally, the variations between EndoWrist tools was not analyzed in this work. A single Maryland Bipolar Forceps was used in testing; future work will explore the variations within this specific tool as well as the variations between different types of tools.

Much work remains to translate this for clinical use, but the merely-minor reduction in estimation accuracy when

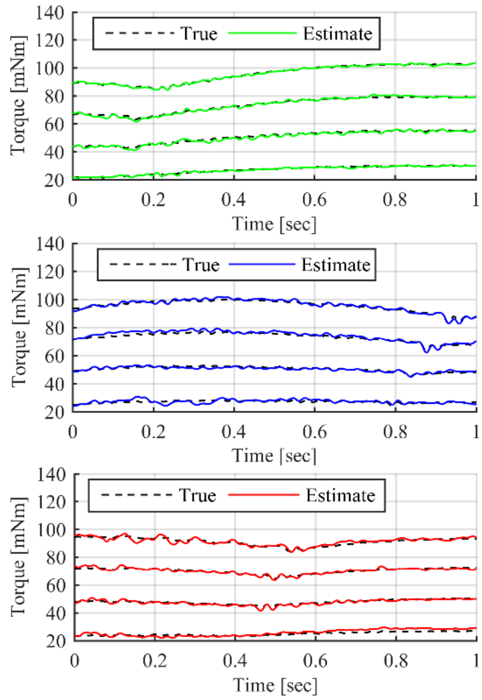

Fig. 3 Time series example data for control (top), experiment 1-varied roll+yaw (middle), and experiment 2-varied pitch+yaw (bottom), for each tested level of torque.

including jaw orientations is encouraging. Previous results in [3] reported three-fold variation in raw grip force, but despite these large variations the estimation technique presented here yields promising results.

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