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A sEMG Proportional Control for the Gripper of Patient Side Manipulator in da Vinci Surgical System

Kehan Yang[1], Tess B. Meier[1], Haoying Zhou[1], Gregory S. Fischer[1], Christopher J. Nycz[1]

Abstract— **There is a large community of people with hand disabilities, and these disabilities can be a barrier to those looking to retain or pursue surgical careers. With the development of surgical robotics technologies, it may be possible to develop user interfaces to accommodate these individuals. This paper proposes a hand-free control method for the gripper of a patient side manipulator (PSM) in the da Vinci surgical system. Using electromyography (EMG) signals, a proportional control method was tested on its ability to grasp a pressure sensor. These preliminary results demonstrate that the user can reliably control the grasping motion of the da Vinci PSM using this system. There is a strong correlation between grasping force and normalized EMG signal (r= 0.874). Moreover, the gripper can generate a step grasping force output when feeding in a generated step signal. The results in this paper demonstrate the system integration of a research EMG system with the da Vinci surgical system and are a step towards developing accessible teleoperation systems for surgeons with disabilities. Hand-free control for remaining degrees of freedom in the PSM is under development using additional input from the motion capture system.**

Keywords: sEMG proportional control, da Vinci surgical system, ROS

I. Introduction

Approximately 541,000 Americans suffered from different levels of upper limb loss in 2005, and the number of cases is expected to double by 2050 [1]. Among those upper limb loss cases, many only experience hand disability. A study in UK and Italy shows that among their yearly upper limb amputation cases, 61% of them are transcarpal, and 2% are wrist disarticulation [2]. In addition, among the 1% to 2% of newborns that are born with congenital defects, 10% have upper extremity malformations [3]. While the number of surgeons effected by limb loss during their career has not been well documented, severe hand disability can put an end to a surgeon's career or prohibit the path to becoming a surgeon altogether. Even after amputation below wrist, most muscles controlling the hand still exist and are functional within the forearm. Moreover, the training and knowledge of surgeons enable them to control those muscles properly and make correct decisions during a surgery. With the help of surgical robotic systems and proper sensors to read muscle signals, it may be possible to help them operate again.

The da Vinci surgical system (Intuitive Surgical, Sunnyvale, CA) is an FDA-approved robotic system for teleoperated minimally invasive surgery. The master tool manipulator (MTM), which the surgeon uses to control the robot, still requires the dexterity of the operator's hands and fingers. Though there are research projects which focus on further developing its control mechanisms, most of the new control interfaces are focused on developing novel control interfaces of the endoscopic camera, new flexible endoscopes, and vision devices. Few focus on the compatibility for surgeons with disabilities [4]. Control of the gripping motion of da Vinci forceps and scissors is currently accomplished through a pinching motion on the MTM. One possible solution for controlling this motion without motion of the user's hand, is through sensing electromyography (EMG) signal from forearm muscle contraction. EMG technology can record the electrical activity produced by skeletal muscles, and the signals can be used to detect abnormalities, activation level, or the biomechanics of human movement [5]. There are two types of EMG electrodes for recording: surface EMG (sEMG) and intramuscular EMG. The non-invasive characteristic of sEMG provides the possibility for its use as a sensor in a device controller. As a limitation, sEMG signal comes mostly from superficial muscles, and the signal strength from the underlying muscles highly depends on the depth of subcutaneous tissue [5].

sEMG is regularly used as an input for human-machine interaction [6]. There are three main usages for EMG signals in the control domain: on-off control, Proportional control, and Multi-State Control [7], [8]. The EMG signal acts as a switch in on-off control to determine the robot states. It is a robust and intuitive method, but the lack of mid-point states narrows its applications [8]. To increase the controllable states of the signal, approaches using classifiers have been implemented to achieve pattern recognition (PR) and move the actuator to a specific state based on PR result [9]–[11]. Both on-off control and pattern recognition use discrete states, while continuous states are preferred in some situations. A proportional control system allows users to change one output of the system by varying their input within a corresponding continuous interval [8]. Proportional control is well suited for controlling the grasping motion of the da Vinci PSM.

Using EMG signal as a proportional control signal source has been well studied. Many prostheses and exoskeletons have used sEMG as a proportional control source. Young et al. developed a controller for a hip exoskeleton using both proportional EMG control and biological torque control and compared their performance [12]. Both controllers helped to reduce metabolic cost, but EMG based control had better performance. Yatsenko et al. built a proportional controller for a prosthetic hand and wrist and tested on three subjects

[1]K. Yang, H. Zhou, and T. B. Meier are with the Robotics Engineering Department, Worcester Polytechnic Institute (WPI). (email: {kyang3, tbmeier, hzhou6, gfischer, cjnycz}@wpi.edu)

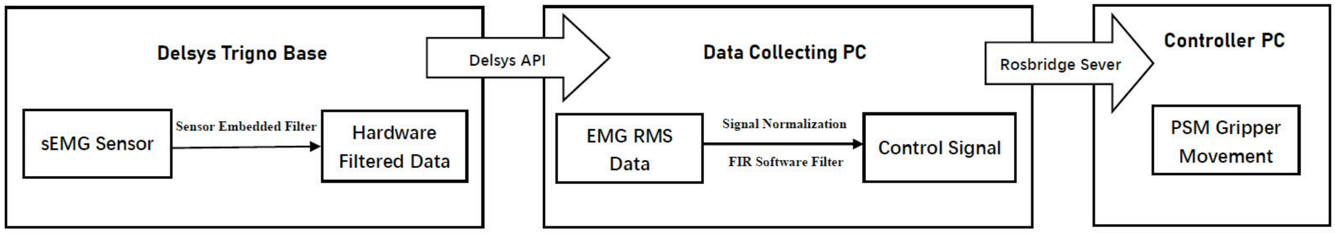

Fig. 1. Plot of General System Structure: The Delsys Trigno system is connected to data collecting PC using serial to USB cable. The data collecting PC is connected to the controller PC through Rosbridge server. The Controller PC holds ros master core, dvrk-ros package, and controlling scripts

including one transradial amputee [13]. They included both wrist movement and hand open/close, and their results were encouraging. For their work, they used 22 electrodes to fully decouple different muscle contractions. Ao et al. developed an EMG-driven Hill-type neuromusculoskeletal model and a linear proportional model for an ankle power-assist exoskeleton robot and compared their performance [14]. Though the combination of sEMG signal and physiological model has a better performance in general, the linear proportional model is reasonable in accuracy as well.

Previous work shows the feasibility of using sEMG signal to map muscle contraction to robot grasping or motion proportionally. However, these proportional controllers have not been investigated for the control of surgical systems. This paper proposes a proportional control method for the grasping motion of a da Vinci surgical system PSM using Delsys sEMG sensors. A preliminary user study was done to demonstrate the system's feasibility.

II. Material and Methods

The main hardware used in this project is Trigno Wireless Biofeedback System (Delsys Inc, Natick, MA), the da Vinci surgical system with da Vinci Research Kit (dVRK) controller boxes [15]. The main software packages used in this project are Delsys API and the dvrk-ros package. Fig. 1 shows the general structure of the proposed control system.

The Trigno system includes a base and 16 wireless Trigno Avanti Sensors. It can output the processed data as analog signals to suitable devices or digitized data via USB. In addition to the hardware sensor system, Delsys, Inc is developing an API for Trigno to help developers access sensor data in custom applications. Its core is written in C# and compiled to dynamic link libraries so that it can be used by multiple languages, including Python which was used for this implementation. A Windows machine was used to receive the EMG data. After filtering and normalizing the received data on the Windows machine, the normalized data was published using roslibpy package to a ROS topic on a Linux machine running dvrk-ros package via Rosbridge WebSocket Server.

The da Vinci surgical system with dVRK is used in this work as a research platform for surgical robotics. It has two parts, the surgeon's console, which includes a stereo viewer and a pair of Master Tool Manipulators (MTM), and a patient-side cart which includes three Patient Side Manipulators (PSM) and a Endoscope Camera Manipulator. To demonstrate the feasibility of this approach the gripper on one PSM was used in these experiments. Zihan et al. from Johns Hopkins University developed a ROS interface for controlling da Vinci surgical system with dVRK called dvrk-ros [15], [16]. In this project, sEMG signal strength is mapped to gripper position. Performance of the proposed method is compared with control by the MTM which uses a position controller.

A. EMG Sensor Placement

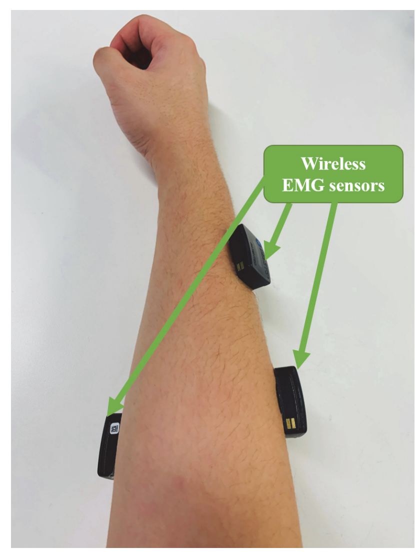

Fig. 2. Delsys Trigno wireless EMG sensors placement on a user's forearm

To cover more superficial flexors and extensors inside the forearm, three sensors are attached to the user's forearm, as shown in Fig. 2. One sensor is placed above flexor digitorum superficialis, another sensor is placed above the extensor digitorum, and the last sensor is placed above extensor pollicis brevis. These muscles are superficial and provide good signal to noise ratio. Sensors were attached using double sided tape after the skin had been shaved and cleaned using an alcohol pad.

B. EMG data filtering

The raw EMG signal is an oscillating signal with a frequency spectrum between 0-500Hz. The raw EMG is filtered to remove inherent noise in electronics equipment, ambient noise, and motion artifact [17]. Of the three noise sources, motion artifact is the most significant. The Avanti Senor has a 20-450Hz band pass filter embedded as signals with a frequency lower than 20Hz are typically due to motion artifacts and the majority of the EMG power is in the range of 50-150Hz. The sensor was set at a sampling rate of 1924Hz and the Delsys API provides an array of the 52 most recent samples every 27ms. A root mean square (RMS) filter was applied to provide a relatively smooth control signal representative of the average power of the EMG signal over a specified window. Due to the array provided by the API, the RMS window in this study is a multiple of 52. A larger RMS window can take more information from the previous state and smooth the output data curve. However, a larger window can also ignore some features and delay the current state. An RMS window length of 108ms (the four most recent raw EMG arrays) that updates every 27ms is used in the control system to balance response and smoothness. An RMS window between 100ms and 350ms is typical in EMG signal processing, with the lower end of the range giving better response [18]. An additional exponential moving average (EMA) filter was applied to the RMS data to provide a more stable control signal. An EMA filter uses information from previous states to adjust the current state. Eq. 1 shows the calculation of EMA.

$$S_t = \begin{cases} Y1, & t = 1 \\ \alpha Y_t + (1-\alpha)(S_{t-1}), & t > 1 \end{cases} \tag{1}$$

The coefficient α represents the degree of weighting decrease, a constant smoothing factor between 0 and 1. A higher α discounts older observations faster. Y_t is the value at a time period t, and S_t is the value of the result from the EMA at any time period t. The larger the coefficient the faster the data will be dampened, but a large coefficient would also generate a delay. Normally the coefficient would be set to achieve the smallest mean squared error (MSE) between original data and filter output [19]. To have a faster dampening response under reasonable (MSE), the coefficient is set to 0.85.

C. EMG signal calibration

After the EMG sensors were attached to a user, the signal strength was calibrated to maintain similar performance among different individuals and different test sessions. All testing was conducted on able bodied individuals. To help these users control their muscle force, a pressure ball was placed in their hand for them to squeeze. The calibration included two sessions of maximum voluntary contraction (MVC) of the muscles for 15s followed by resting for 10s. The data collected was divided into relax and max contraction groups. An average of the processed EMG signal for resting and MVC states were used to normalize the control signal between 0 and 1.

D. Mapping EMG Signal to Control Signal

Once a filtered and normalized EMG signal was collected, it was mapped to the position of the da Vinci PSM gripper.

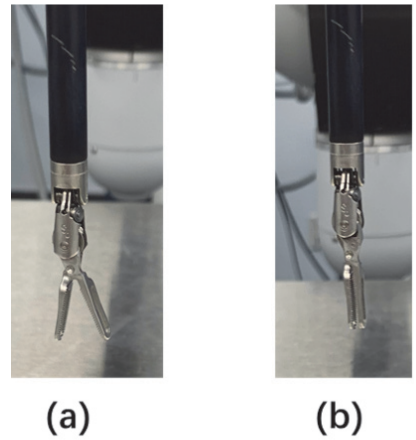

Fig. 3. (a) Gripper fully open. (b) Gripper fully close

As shown in Fig. 3, the related position of the gripper is 30 degrees as fully open and 5 degrees as fully closed. The relation between EMG signal strength and gripper position is mapped based on the equation of a line. To allow finer control of force applied to a grasped object, a contact detection based piecewise function was used. The program tracks the position error of the gripper as the difference between desired position and current position as read from its encoder. As shown in Fig. 4, the gripper will close faster before contact. When the position error is larger than a threshold, it will reduce the slope of the mapping function allowing for smaller adjustments in gripper position after contact.

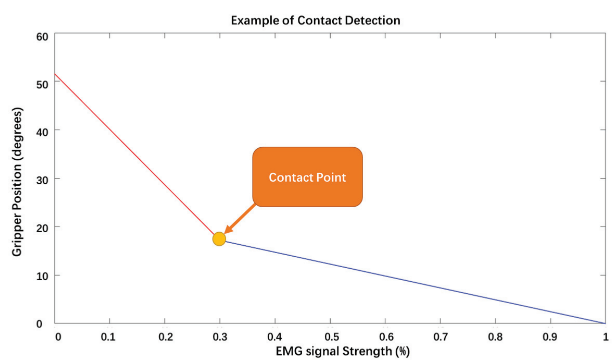

Fig. 4. A demonstration of the mapping of processed EMG signal to gripper position. The gripper will make smaller motions after contact is detected.

DVRK provides servo control that directly applies current to motors for real-time control. A large step, low update rate using servo control is not advised as it might result in a large current impulse and damage to the motors. Normally, an update rate of 200Hz can reduce the step difference enough to keep motor current within safe operating limits. Since the feedback rate of the Delsys API is fixed at 37Hz, instead of directly moving the gripper to the next desired position every 27ms, the control program linearly interpolates between the current and desired position with 8 discrete steps. This increases the control loop running rate to about 296Hz but

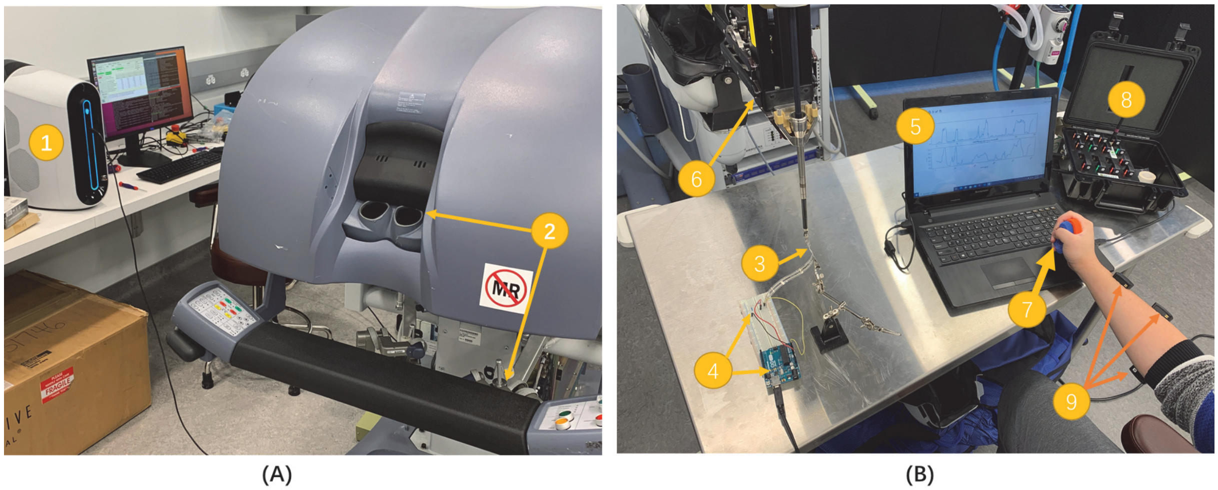

Fig. 5. System setup for user study trials. (A1) Linux machine that runs dvrk-ros package and Rosbridge server. (A2) Stereo viewer and one of Master Tool Manipulator. (B3) Silicon Wrapped FSR. (B4) Arduino UNO and voltage divider circuit. (B5) Windows machine that collects, processes and transfers EMG data and provides visual feedback for subject. (B6) A patient side manipulator. (B7) Pressure ball for hand functional user to better control their grasping. (B8) Delsys Trigno system. (B9) Active Avanti EMG sensors.

Fig. 6. The silicone coated Flexiforce Standard Model A201 FSR used for testing grasping force.

introduces an additional delay.

E. Force Reading

To test the performance of the proportional EMG control system, a force sensitive resistor (FSR) was used to measure the grasping force of the PSM. To better stimulate grasping of soft tissue, the FSR (FlexiForce Standard Model A201, Tekscan Inc., Boston, MA) had an approximately 2.5mm silicon layer applied to each side, as shown in Fig 5.

Each brand and model of FSR has its specific force-conductance curve, and can be found from their documentation.[1] The force-conductance curve for the sensor used in this experiment can be regarded as an equation of a line as follows:

$$G = 0.00014 * F + 0.0012 \tag{2}$$

Where G is the conductance of the sensor and F is the force in Newtons on the sensor surface.

Equation 2 indicates that we must know the conductance of the FSR sensor to calculate the force reading. This project uses a voltage divider circuit with a pull-down resistor of 2 MΩ to measure the voltage change on the FSR sensor. An Arduino Uno was used to read the analog voltage signal and calculate the applied force. Further calibrations of the sensor were not performed, as it was being used for comparative measurements where the absolute value was not critical to the testing result. The measured force was presented on a plot to the person controlling the system.

[1] https://cdn.sparkfun.com/datasheets/Sensors/ForceFlex/FLX-FlexiForce-Sensors-Manual.pdf

F. Experimental Setup

In order to test the controllability of the system, an experiment was designed and carried out. Fig. 6 shows the experimental setup of the proposed system. For each user trial, after calibrating the EMG signal, users were asked to reach and stay at different contraction levels of grasping force for a period of time. Subjects were also asked to perform the same task using the MTM control method to compare the system performance with the original control method of the da Vinci surgical system. In addition to the user study, a simulated step EMG signal was applied to the proposed control pipeline to study the relationship between EMG signal strength and grasping force.

III. Results and Discussion

Three of the authors performed preliminary testing of the system performance. One subject's experimental results are shown in Fig. 7 and Fig. 8. All subjects were able to reach and maintain three different grasping force levels of low, medium, and high (one-third, two-thirds, and maximum grasping force), using both the EMG control method and the MTM control method. The average Pearson correlation coefficient between the grasping force of PSM and normalized EMG signal is 0.874. Subjects were allowed to practice on the system until they self-reported that they felt proficient in controlling the gripper position. The average time of this practice was approximately 5 minutes. After approximately 10 minutes of controlling the gripper using the proposed method, two of the subjects reported tiredness and muscle soreness.

The first plot in Fig. 7a and Fig. 8b are from the same session using EMG control. Fig. 7a shows the relationship between EMG signal strength and force sensor reading, while

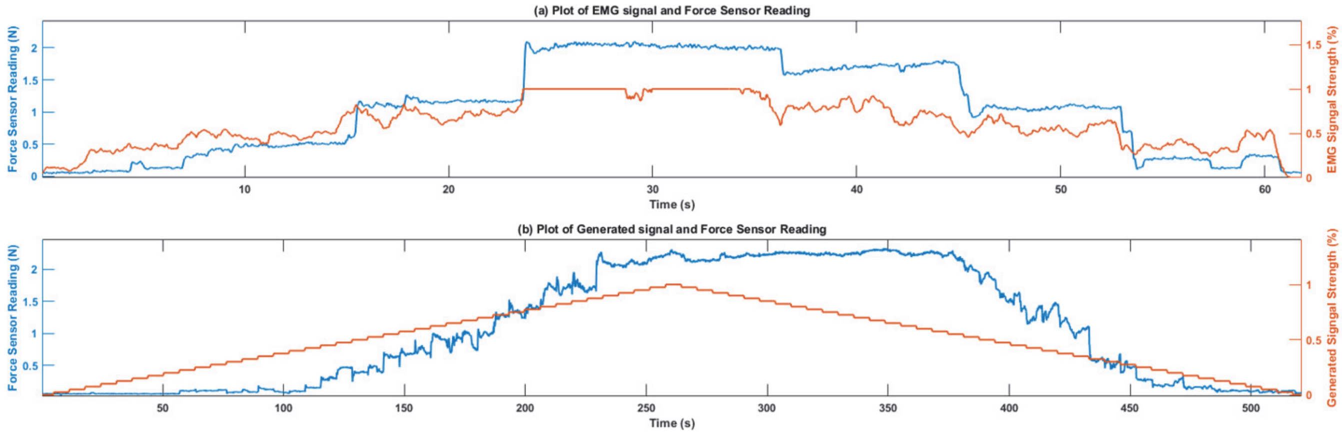

Fig. 7. Relationship between force sensor reading and normalized EMG signal. (a) Normalized EMG signal input from a subject. (b) Simulated step signal input.

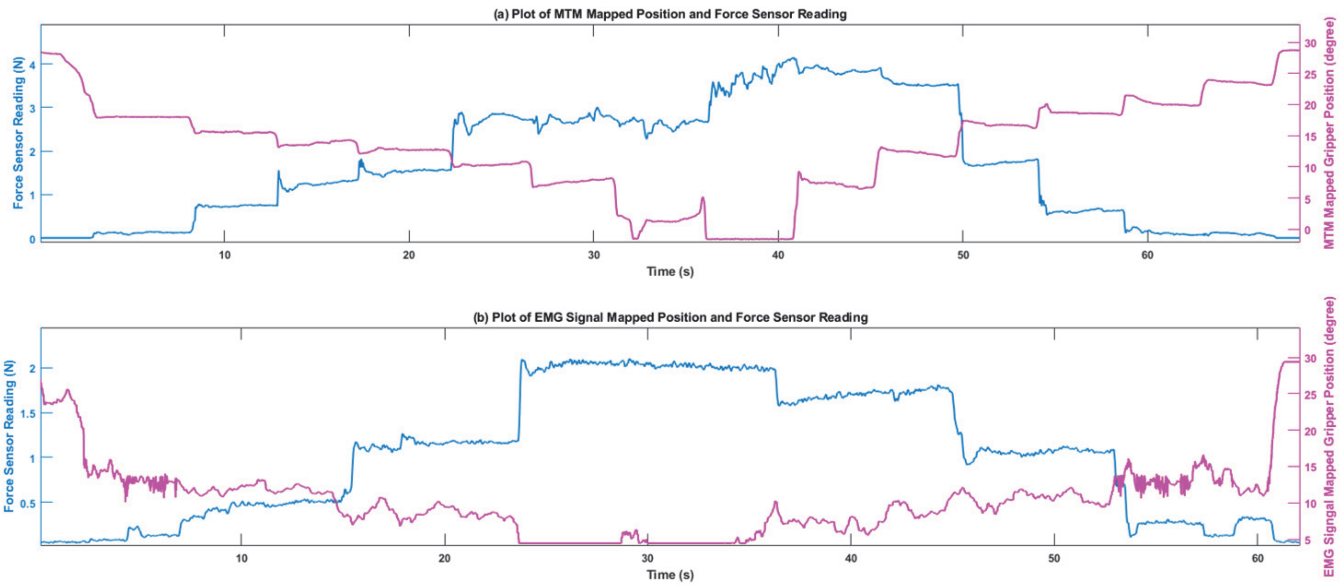

Fig. 8. Relationship between force sensor reading and PSM gripper position setpoint. (a) MTM control method PSM gripper position setpoint input. (b) EMG control method PSM gripper position setpoint input.

Fig. 8b shows the PSM position setpoint and force sensor reading. These two figures, demonstrate that a subject can maintain different force levels for a period of time. Fig. 7b shows the relationship between EMG signal and grasping force when a simulated step signal is applied to the robot controller. For different signal levels, the gripper applies a related grasping force up to a point of saturation. Friction and backlash in the system are evident as the measured force follows a different curve for increasing control setpoint than it does for decreasing setpoint. The friction and backlash causes force to be maintained for a period as the position commanded of the gripper decreases.

The plots in Fig. 8 can help compare the performance between the original MTM control and the EMG control method. Though both succeed in generating different levels of grasping force, MTM control has almost no delay whereas the EMG control has a delay of about 200ms due to filtering, latency, and interpolation. The maximum force for MTM is almost twice the proposed method, however this is because the position setpoint limit for the MTM controller allowed for values below 0 degrees while the EMG controller never reached below 5 degrees due to mapping setup. The force results are close when comparing the force sensor reading from both methods at a 10 degrees position setpoint for the gripper.

IV. Conclusion and Future Work

This paper proposes a system architecture and signal processing for EMG control of a PSM gripper of the da Vinci surgical system. Users were able to demonstrate control over the force applied to a compliant pressure sensor. Though the clinical da Vinci Surgical System does not provide force feedback to the user, visual inspection of tissue deformation and control of gripper position does allow for a coarse degree of force control in the clinical setting. This functionality was preserved through the EMG control implemented. Though under current hardware and software structure its performance does not match that of the original da Vinci MTM, the results validate the feasibility of controlling portions of a surgical robot using EMG signals. Further refinement of these concepts may lead to control interfaces which are more accessible for surgeons with hand disabilities.

Future work will focus on reducing operator fatigue, reducing latency, and compensating for cross-talk from adjacent muscle contractions. Targeting different muscle groups, or providing different scaling of EMG signal to control input may reduce operator fatigue. Improvements in software and hardware implementations can reduce latency. Combining pattern recognition with proportional control could help classify muscle signals generated by cross talk from adjacent muscles and those intended for gripper control.

In addition to refining the current gripper control, additional control methods for the entire PSM arm are needed. EMG is useful for controlling one joint but challenging to replicate the total arm movement. A promising direction for achieving full arm control is combining Motion Capture System with EMG proportional control. In this arrangement, movement of the operator's arm will be measured by motion capture to control the position and orientation of the PSM with EMG used to control the opening and closing of the gripper. With this complete implementation, control of a da Vinci PSM for surgical tasks may be possible for individuals with hand disabilities.

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