NEEDLE INSERTION FORCE MODEL FOR HAPTIC SIMULATION

ADAM GORDON
SPRING 2015

A thesis
submitted in partial fulfillment
of the requirements
for baccalaureate degrees
in Mechanical Engineering and Bioengineering
with honors in Mechanical Engineering

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ABSTRACT

Many percutaneous medical procedures rely upon clinicians performing precise needle insertion in soft tissue. The utility of haptic simulation systems in training clinicians for these procedures is highly dependent upon the ability to render accurate insertion force feedback. This thesis presents a piecewise mathematical model for insertion force that does not require tissue material properties, detailed mechanical approximations, or complex computations. Through manipulation of model parameters, a wide variety of insertion tasks and clinical scenarios can be modeled. A MATLAB based algorithm was developed to estimate the model parameters required to replicate experimentally measured needle insertion forces. Laboratory based insertion experiments were then conducted with several combinations of needle and tissue types, including both artificial and animal tissue. Using the MATLAB algorithm to estimate model parameters, the model was found to replicate the measured insertion forces with an average absolute mean error of less than 0.05N in 11 of 12 needle and tissue combinations tested. Upon validating model adaptability to different insertion tasks, the ability to deliberately manipulate the model to simulate clinical variability was demonstrated. Through modification of model parameters, a model of porcine skin insertion was altered to reflect a thicker tissue sample and a stiffer tissue sample. With further development, the potential utility of this model in simulation training is two-fold: simplicity in adapting to train different insertion procedures and enhanced training through manipulation of specific features of insertion forces.
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ACKNOWLEDGEMENTS

There are several individuals I would like to thank for their tremendous support in this project and the writing of my thesis. First, I would like to thank Dr. Jason Moore for all of his support and guidance, not just on this project as my thesis supervisor, but also throughout my four years working in his lab. The mentorship and experience I have received while working in the Precision Medical Instrument Design Lab has been invaluable to me as an engineering student. I know that all of the skills and knowledge I have acquired through working with him will serve me well no matter where my future career takes me. I would also like to thank Andrew Barnett and Inki Kim for all of their assistance throughout the project.

I would also like to thank Dr. Hosam Fathy for serving as my honors adviser in Mechanical Engineering and helping me revise this thesis to its final form. The insightful advice he has offered me throughout my college years has always been extremely helpful when making career and academic related decisions.

Finally, this thesis and all that I have been able to achieve at Penn State would not have been possible without the loving support of my family. To my parents, brother, and grandmother, I am eternally grateful for all that you have done to help me get where I am today. I also must acknowledge my late grandfather, Tedric A. Harris, whose passion for engineering and life has always inspired me to strive to be the best person I can be.
Chapter 1
Introduction

1.1 Clinical Background

Central Venous Catheter insertions are performed over 5 million times per year in the United States [1]. While these procedures deliver essential medical care, mechanical complications, including arterial puncture, hematoma, and pneumothorax, have been reported at rates ranging from 5% to 21%. [1-3]. The occurrence of such complications has been correlated directly to clinician experience and training methodology, highlighting the need for medical simulation technology [2, 3]. In addition to Central Venous Catheter insertions, many percutaneous procedures exist that rely upon accurate placement of surgical needles, including tissue biopsy, brachytherapy, ablation, and lumbar puncture [4, 5]. Given that physicians rely heavily upon haptic perception to guide these needle insertions, accurate force feedback is a key element in computer based simulation systems [6]. To provide this feedback, a model for needle insertion force into soft tissues is required.

1.2 Existing Methods of Modeling Needle Insertion Force

Modeling the force interactions during needle insertion into biological tissue has been a focus not just for medical simulation, but also for robotic surgery and preoperative planning [7]. Finite Element Methods (FEM) have been the focus of many works for modeling needle insertions and resulting tissue deformations. A common strategy has been to create a mesh framework representative of tissue, some works also adding a distinct mesh for the needle, with needle interaction forces simulated by boundary conditions applied to appropriate nodes [8-12]. Recent studies have also explored using advanced forms of FEM to more accurately simulate the needle insertion fracture mechanisms [13, 14]. Although it is a
common simulation technique, there are major challenges associated with FEM. First, implementing accurate tissue constitutive equations is extremely difficult, as real tissue exhibits nonlinear and viscoelastic behavior [15]. While some models have incorporated a form of nonlinearity or viscoelasticity [13, 16-18], many instead approximate the tissue as linear elastic material [8-10, 14]. Due to large material deformations in certain clinical scenarios, these approximations are not always appropriate [17]. Second, FEM techniques for needle insertion have been widely acknowledged to have costly computational demand, sometimes inhibiting real-time simulation. For this reason, a significant focus of recent research has been on improving the computational efficiency of these methods [16, 18-20]. Lastly, model accuracy in FEM requires accurate estimation of tissue mechanical properties. These estimations are challenging due to patient variability, biological variation in testing conditions, and tissue inhomogeneity [21, 22]. Many FEM models simplify this problem by assuming homogenous properties for regions of the same tissue type [10-14]. This comes at the expense of losing some of the inherent variability in insertion forces, such as those caused by anatomical substructures like vasculature, which have been shown to cause large peaks in insertion force [23].

In addition to FEM, there is a range of other models developed for needle insertion forces, several of which were developed with the potential to be implemented alongside FEM. A key model cited in many works divides the needle force into three sub-forces applied in a piecewise fashion: tissue stiffness, friction, and cutting. Stiffness force is modeled according to a second order polynomial, friction force is modeled by a Karnopp model, and cutting force is a constant [7]. In a similar model, this was extended to multiple layers of tissue with function parameters specific to each layer [24]. Within the realm of these schemes, the modeling of friction sub-force has been its own concentration of recent research [25, 26]. A notable limitation in this three force method is the absence of collisions with small internal structures that lie within a tissue layer and may influence insertion force [7].

To simplify the relationship between needle penetration depth and force, Hookean spring models have been another common theme in insertion force modeling. To simulate the needle passing through
different tissue types, the spring constant varies for each tissue layer. Transitions between layers may be incorporated with empirical modifications to the overall force [27-29]. In some models, a linear viscous damping is also substituted for the fat layers. It is important to once again note that Hookean relationships are accurate for tissue only if small deformations occur in each layer, which is not always the case in a clinical situation [29]. In a more advanced form of the above layer modeling, a series of Voigt elements is used to capture some of these nonlinearities [30].

Online estimation in combination with a parameterized needle insertion model is a more complex method of mathematically modeling forces. In one instance, parameters were used that varied with time. This is impractical for force simulation applications, as parameters will have more data points associated with them than an original force data set [31]. Similar work utilized steady state convergence parameter values [4]. Another mathematical approach used a radial basis function network to form a non-linear approximation of insertion force [32]. Both of these approaches have yet to be demonstrated on real, inhomogeneous tissue.

In systems with advanced graphic renderings, insertion forces have been simulated using proxy-based algorithms. In general, proxies are assigned based upon the positions of graphical objects in the simulation, and the simulated needle tip position is virtually coupled to a proxy using a damper-spring combination. The force within this coupling dictates the force output of the simulation, and when it exceeds a given threshold, surfaces, such as an organ capsule, may be penetrated [33]. Parameter constants are assigned to each proxy coupling based upon the material properties of the graphical object interacting with the needle [34].

Other studies have focused on modeling the distribution of force over the length of the needle, with total insertion force coming from the integration of this distribution. The parameterization of these distributions is also dependent on approximating individual tissue as linear elastic material with uniform properties [35, 36].
1.3 Overview of This Research

In this thesis, a modeling system for needle insertion force simulation is presented in which forces are parameterized according to a piecewise mathematical function. Through parameter manipulation, this model can replicate axial insertion force as a function of needle depth for a variety of insertion tasks. This manipulation also enables deliberate modification of insertion force features to simulate the high clinical variability in insertion procedures, which has been identified as a crucial element in clinician training [37]. Unlike the common existing models, this method, combined with a simple parameter fitting scheme, does not rely upon complex computation, determination of material properties, or detailed mechanical approximations.

Through a series of needle insertion experiments, the applicability of this model to several tissue types and needle geometries will be demonstrated and analyzed. First, the model function and the associated parameter estimation algorithm will be described. Next, the experimental procedure for measuring insertion forces and obtaining model parameters will be outlined. Third, the effects of the variable settings of the estimation algorithm on the resulting model parameters will be explored and optimized. Upon selecting settings for the estimation algorithm, the ability of the model to replicate the experimentally measured forces will be analyzed and discussed. After validating the ability of the model to replicate the measured insertion forces, a demonstration will be performed of manipulating the model to simulate clinical insertion force variability. Finally, conclusions from this work and directions of future study will be presented.
Chapter 2

Tissue Insertion Force Model

2.1 Overview of Model

The model presented in this paper estimates the total axial force acting on a needle as a function of the needle’s insertion depth along a one dimensional path. In many insertions into animal tissue, such as that shown in Figure 1, the observed insertion force changes rapidly in a discontinuous fashion as various anatomical structures are being cut or punctured. The patterns of these discontinuities may vary considerably from one insertion to the next, even in the same tissue samples. Often, these discontinuities, such as non-linear peaks in force, can serve as critical haptic cues in the clinical setting [31, 37].

![Graph showing needle insertion force vs. depth](image)

**Figure 1: Axial needle insertion force for 18G brachytherapy needle in bovine liver**

In order to capture the overall discontinuous and non-linear nature of needle insertion forces, an exponential function is applied in a piecewise manner over the length of an entire needle insertion task to obtain needle insertion force:
Here, $F$ is the axial insertion force as a function of needle insertion depth $x$, where $x$ is zero when the needle first contacts tissue. $A_n$, $B_n$, $C_n$, and $D_n$ parameterize the force in each piecewise interval $n$. The critical depth at which each piecewise interval terminates is denoted by $P_n$. In modeling force as a function of solely insertion depth, the assumption of a constant, given insertion velocity is made for simplicity. Future work may study the velocity dependence of model parameters. In addition, the one dimensional nature of the model makes it appropriate only for simulations in which three dimensional needle manipulation for needle steering is not required.

2.2 Model Parameter Estimation Algorithm

To obtain the model parameters for a real insertion task, a MATLAB based algorithm, shown in its entirety in Appendix A, was developed and implemented. With measured force versus depth data input into the MATLAB program, all model parameters necessary to replicate the measured data are automatically generated in addition to the resulting modeled force at each position. As shown in Figure 2, this program is highly effective in estimating the model parameters for starkly contrasting needle insertion force profiles. Using this algorithm in combination with experimental data provides a means to demonstrate the effectiveness of the proposed model in replicating insertion force in a wide range of insertion scenarios.

The MATLAB code can be broken down into three main sections. The first section (Line 3) determines where to segment the data into piecewise intervals, thus providing initial values for $P_n$. Simultaneously, it fits the exponential function to each interval. The second section (Line 84) corrects the parameters $P_n$ using the intersection points of each interval’s function. This prevents abrupt changes in
force values between piecewise phases. Finally, with all model parameters determined, the model function is applied to positional data to generate the model predicted force at each insertion depth (Line 114).

![Graph A](image)

![Graph B](image)

Figure 2: Measured insertion force and modeled insertion force for (A) 18 gauge conventional hypodermic insertion through porcine skin and (B) 18 gauge brachytherapy needle insertion into bovine liver; Critical depths, Pn, marked with red circles

2.2.1 Initial Segmentation and Curve Fitting

Prior to determining model parameters, the measured force data is filtered using a second order, low-pass Butterworth digital filter in a built in MATLAB function (Line 4). The cutoff frequency is dictated by a parameter on a normalized range of 0 to 1, where 1 corresponds to the Nyquist frequency, or half the
sampling rate, and 0 corresponds to 0 Hz. During analysis performed in this work, this cutoff value was varied between 0.1 and 0.9. As will be shown in the following sections, insertion force data, particularly in real tissue, is subject to high frequency, low amplitude fluctuation that is caused not just by sensor noise, but also by inherent instabilities in cutting force. Filtering out this noise enables the model to better reflect the more critical global trends in the needle insertion force that likely serve as the key haptic cues in a clinical setting.

After filtering the data, the algorithm starts by taking the first five data points and performing a non-linear least squares curve fit to the exponential function of the first piecewise interval of the model (Line 28). Following the curve fit, the exponential function parameter values that model the first five points are stored (Line 30) and used to generate the model predicted force over the first five data points (Line 32). The absolute error between the model predicted force and measured force at the fifth point is then calculated (Line 33). This process repeats itself within the while loop of Line 24, and with each iteration of the loop, an additional four points are added to the data range over which the first piecewise phase of the model is fit. The location of this range in the data array is stored in the code using the variables $z$, which is the array position marking the beginning of the range, and $j$, which marks the end of the range. During each iteration of the while loop, the model parameters of the first phase are updated to reflect the non-linear least squares fit over the current data range. When the error calculated at the final point of the data range exceeds the established threshold value, the loop is stopped. The value of this error threshold was varied for study during this work between 0.01 N and 0.13 N.

Upon first crossing the error threshold, the algorithm proceeds to another while loop that fits the data range of the first piecewise interval to the exponential model function (Line 59). This second loop starts by fitting the data range that was last fit by the first loop, but it excludes the final four data points of that range. The second loop follows the same iterative process of fitting the model function and checking absolute error, except only one data point is added to the data range between iterations instead of four (Line 67). The loop terminates when the error threshold is crossed, and by advancing only one data point at a
time, the exact position at which the error threshold is crossed is found. In this dual loop configuration, the computation time of the algorithm is significantly reduced. It first proceeds through the data in a coarse manner, advancing four points at a time. Upon finding the error threshold has been crossed, it revisits the previous four points in a fine manner, advancing only one point at a time to find the exact position where the crossing occurs.

Once the while loop of Line 59 is stopped at the point where the error threshold has been crossed, the algorithm stores the model parameters for the first piecewise segment and stores a preliminary value for the first critical depth, $P_f$ (Line 75). This initial value of $P_f$ is defined to be the insertion depth of the data point that marks the end of the data range immediately before the error threshold was crossed. The positions of critical depths, $P_m$, are marked in the insertion trials of Figure 2 with red circles. Next, the algorithm returns to the initial curve fitting while loop (Line 24), where it restarts the process by fitting the first four data points of the second piecewise interval, which immediately follows $P_f$. The two curve-fitting while loops continue until the entire set of force data has been processed.

During preliminary testing of the algorithm, it was found that the error threshold condition alone was not enough to adequately segment the graph into piecewise sections. Specifically, the resulting model parameters did not consistently capture the data points in real tissue insertion that mark the insertion force rapidly falling due to puncture through a tissue membrane layer or portion of vasculature, such as that shown in Figure 3. The cause of the deficiency was that this release in force occurs so rapidly that the downward slope of the force profile following a peak contains only a few data points. Following a piecewise segmentation at a peak, the algorithm progresses from fitting just the downward sloping portion to also fitting the plateau. Due to the scarcity of data points in the downward sloping portion, the least squares fit no longer produces any modeled force values between the peak and the plateau once the plateau is included in the fitting range. This may happen without ever crossing the error threshold, as only the final data point of the fitting range is checked for crossing the threshold. To prevent this occurrence, another condition was
needed to separate the downward sloping region and the proceeding plateau into different piecewise intervals of the overall model.

One of the key mathematical markers of a rapid release of force being followed by a plateau is a sharp decrease in the magnitude of the first derivative of the insertion force with respect to position. Consequently, the algorithm was modified to check for this derivative change condition and use it to trigger the start of a new piecewise phase of the model. Within the first model fitting while loop (Line 24), the first derivative of the modeled force is calculated at the end of the data range of each iteration (Line 35). With end of the data range marked by array position \( j \), the modeled force represented by \( F \), and the insertion depth represented by \( x \), an average derivative over the final four data points of the data range is calculated as follows:

\[
\left. \frac{dF}{dx} \right|_{x=j} = \frac{F_j - F_{j-4}}{x_j - x_{j-4}} \quad \text{(Equation 2)}
\]

During the fitting of each piecewise interval, the second iteration of the Line 24 while loop stores the absolute value of this derivative as a reference (Line 37). Coming from the second iteration, this reference derivative would represent the slope of the force immediately after a transition between model intervals, such as would occur following a peak in force. In each of the proceeding Line 24 while loop iterations, the first derivative is calculated in the same manner and compared to the reference value (Line 40). If the derivative is negative, indicating a downward slope, and has a magnitude that is a very small percentage, 0.5%, of the reference, then a binary variable is changed from 0 to 1 in order to indicate that a transition from a large downward slope to a plateau has occurred (Line 43). Under this condition, the while loop of Line 24 is terminated, and the algorithm skips immediately to Line 75 where it stores the data point position before the transition occurred as a critical depth, \( P_n \). The algorithm then advances to fitting the next model interval, just as if an error threshold had been crossed. In summary, either an error threshold crossing or the
detection of a sharp downward slope followed by a plateau will trigger a piecewise segmentation of the model, allowing the algorithm to proceed to fitting the next piecewise phase.

![Figure 3: 18G brachytherapy needle insertion into bovine liver demonstrating rapid release in insertion force following puncture of a membrane](image)

In order to ensure that piecewise segmentation due to a derivative change occurs only immediately after a peak, another binary variable is used. The variable changes state from 1 to 0 to indicate that the most recent segmentation occurred due to a derivative change (Line 44), and it changes from 0 to 1 to indicate that the previous segmentation occurred due to an error threshold crossing (Line 67). The if-else structure on Line 40 requires this variable to be 1 in order for the derivative change to trigger segmentation. This ensures that the derivative change does not trigger consecutive model segmentations that are unnecessary between the start of the plateau and the proceeding data.

### 2.2.2 Correction of Critical Depths, $P_n$

Upon reaching the second main portion of the MATLAB code (Line 84), the algorithm has determined preliminary critical depths, $P_n$, and defined the exponential function parameters that best fit each set of data between these critical depths. However, at this stage of the algorithm, the modeled force is
defined such that there is no guarantee of an intersection of the modeled force values at the boundary of two adjacent piecewise segments. The modeled force at this stage is shown in Figure 4A, where it can be seen that there are large gaps in the modeled force at the boundaries between piecewise segments.

To correct this and allow there to be fluid transitions between adjacent piecewise intervals, the for loop of Line 86 cycles through each boundary and finds the intersection of the exponential functions that define the modeled force in each adjacent piecewise interval. This is accomplished by setting the equations of adjacent segments equal to each other, then solving for the position of intersection using the default \textit{fsolve} function of MATLAB (Line 90). This intersection position does not necessarily correspond to the insertion depth of a measured data point. To facilitate easy subsequent model analysis, the data point with the insertion depth nearest to the intersection is found (Line 94), and this insertion depth for each boundary becomes the corrected value of $P_n$ (Line 96), as shown in Figure 4B. In some instances, adjacent functions do not intersect, in which case the position at which they come closest in force is defined as the intersection. If the corrected $P_n$ value is less than the value of $P_{n-1}$, then the corrected $P_n$ is reverted back to its uncorrected value (Line 98). This also happens if the corrected value of $P_n$ is greater than the uncorrected value of $P_{n+1}$.

Without this adjustment, there is a high probability that the piecewise intervals of the model will overlap, resulting in an over-defined piecewise function. This correction is essential to ensure that over a given positional range, the modeled force is only defined by a single interval function. After correcting the position of the piecewise boundaries, the final critical depth value is defined as the end position of the measured data. With the completion of this process, the model parameters for a given set of insertion data have been completely defined.
2.2.3 Generating Model-Predicted Force

In the final stage of the model parameter estimation code, the for loop of Line 117 cycles through each critical depth $P_n$. It defines the model output over the range $P_{n-1}$ to $P_n$ as a function of insertion depth given by $A_n e^{B_n(x-D_n)} + C_n$. Once the final critical depth has been reached, the insertion force over the entire insertion trial has been modeled. The model error at each data point is calculated by subtracting the modeled force from the measured force at each position. To quantify overall model accuracy, the absolute mean error is calculated by summing the absolute value of the error at each point, then dividing by the number of data points.
Chapter 3

Experimental Setup for Insertion Force Measurement and Parameter Estimation

3.1 Needle Insertion Setup

The laboratory setup shown in Figures 5, 6, and 7 was utilized to measure axial insertion force as a function of insertion depth in tissue samples. A linear actuator (Dunkermotoren) drove the needle into samples at a controlled constant velocity. To measure insertion force, a six-axis load cell (ATI) was directly coupled to the base of the needle. A LabView interface and data acquisition system (National Instruments, PXIe-6361) operated the actuator and recorded data.

Needle insertions were performed on four different tissue types: bovine liver, porcine skin, homogeneous phantom gel (M.F. Manufacturing Company), and a catheter insertion training mannequin (CAE Healthcare, BPH 660 Series). The phantom gel, shown in Figure 6, was made of polyvinyl chloride modified with plastisol and formulated with a 5:1 plastic to softener ratio. This gel has been commonly used as a soft tissue simulant for needle insertion experiments [38, 39]. The CAE Healthcare mannequin is a popular catheter insertion training tool that simulates relevant anatomical features, including an artificial artery and vein, surrounded by synthetic material. To simulate patients with excess body fat, a fat simulating add-on layer, shown in Figure 7B, can be optionally placed on the surface of the mannequin.

While the artificial tissues did not require any fixture for the insertion experiments, specialized fixtures were employed to constrain the biological tissues. As shown in Figure 5A, the bovine liver sample was placed in a plastic prism with slots on either side to allow needle insertion. To prevent movement within the prism, the top plate of the prism applied a constant pressure of 25 psi through use of a pneumatic pump. For the porcine skin setup shown in Figure 5B, two aluminum plates clamped the tissue to secure it in a stationary position. Insertion holes uniformly distributed around the periphery of the plates allowed the
needle to pass through the front plate, into the skin, and exit through the back plate. The entire fixture could be rotated to align the needle with a new hole after each trial, facilitating an efficient repositioning of the tissue between trials.

Figure 5: Needle insertion experiment setup for (A) bovine liver and (B) porcine skin

Figure 6: Needle insertion experiment setup for phantom gel

During all insertion trials conducted in this work, the linear slide was programmed to insert the needle at a constant velocity of 8 mm/s, a velocity within the range for clinical procedures [40]. Data collection was initiated prior to the needle first contacting the tissue sample, and was terminated upon the
needle coming to a complete stop after reaching its maximum insertion depth. Data was recorded by the LabView program at a 100 Hz sampling rate for all trials. In between individual insertions into the same tissue sample, the tissue was repositioned to prevent consecutive insertions along identical paths. Should trials have been repeated along the same insertion path, the measured force may not have accurately represented a normal insertion, as the tissue would have already been mechanically degraded. The repositioning also added variability to measured insertion forces from one trial to the next, which was desirable given the objective of demonstrating the model’s ability to adapt to clinical variation. For example, repositioning the mannequin caused the needle to puncture the simulated internal artery in some trials, but miss it in others. This resulted in starkly contrasting force profiles measured from one trial to the next, as shown in Figure 8.

Figure 7: Needle insertion experiment setup for the CVC insertion training mannequin (A) without additional fat layer and (B) with additional fat layer
Figure 8: Differences in measured insertion force due to interaction with synthetic artery for 18G catheter hypodermic needle into the mannequin without fat

3.2 Experimental Design

The combinations of needles and tissues tested are shown in Table 1. Five trials were performed for each combination. The mannequin was tested in two configurations: with and without the add-on layer that simulates patients with excess fat tissue. Images of the needles utilized in experiments and their bevel geometries are shown in Figure 9. Following experimentation, insertion force data sets were input into the MATLAB algorithm to obtain model parameters for each trial. As previously mentioned in Section 2.2, the error threshold and filter cutoff frequency in the parameter estimation algorithm can be varied, potentially changing the model parameters found for a given trial. Consequently, for each individual insertion trial, the measured data was processed through the algorithm with each possible pair of error thresholds of 0.01 N, 0.04N, 0.07N, 0.1N, and 0.13 N in combination with frequency cutoffs of 0.1, 0.3, 0.5, 0.7, and 0.9. These normalized cutoff settings correspond to actual frequencies of 5 Hz, 15 Hz, 25, Hz, 35 Hz, and 45 Hz respectively for the sampling rate used in these experiments. Performing these sweeps with estimation algorithm settings allowed the impact of the settings on the estimated model parameters to be understood. As a result, the optimal algorithm settings could be determined for estimating the model parameters needed
to replicate various insertion tasks. With the optimal settings selected for the parameter estimation algorithm, the model parameters and resulting modeled forces were obtained for every insertion trial. These modeled forces were used in section 4.2 and 4.3 to study the effectiveness of the proposed model.

Figure 9: Needles used in experiments and enlarged images of their bevel geometries

Table 1: Needles and Tissue Combinations Tested

<table>
<thead>
<tr>
<th>Needle</th>
<th>Clinical Use</th>
<th>Tissue Tested</th>
</tr>
</thead>
<tbody>
<tr>
<td>18 Gauge Conventional Hypodermic</td>
<td>General Use</td>
<td>Bovine Liver, Porcine Skin, Mannequin W/ Fat, Mannequin No Fat, Phantom</td>
</tr>
<tr>
<td>18 Gauge Prostate Seeding Needle</td>
<td>Brachytherapy</td>
<td></td>
</tr>
<tr>
<td>18 Gauge Catheter Hypodermic</td>
<td>Catheter Insertion</td>
<td>Mannequin W/ Fat, Mannequin No Fat</td>
</tr>
</tbody>
</table>
Chapter 4

Results and Discussion

4.1 Study of Estimation Algorithm Parameters

4.1.1 Effects of Estimation Algorithm Parameters on Model Outcomes

The data from each needle insertion trial was input into the parameter estimation algorithm multiple times, each with a different combination of error threshold and cutoff frequency settings as mentioned in section 3.2. For a given insertion trial, the two most quantifiable indicators of the settings’ effect was the resulting model’s absolute mean error and number of piecewise intervals. It should be noted that the number of piecewise intervals is equivalent to the number of critical depth points, $P_n$. For each insertion trial, the absolute mean error and number of piecewise intervals in the estimated model was recorded at each possible combination of error threshold and cutoff frequency, and then tabulated to obtain graphs such as those shown in Figures 10 through 13. For each individual trial, four such graphs were produced: model error versus error threshold, model error versus cutoff frequency, number of piecewise intervals versus error threshold, and number of piecewise intervals versus cutoff frequency. Appendix B contains these graphs for each of the five 18G brachytherapy needle insertions into bovine liver and each of the five 18G catheter needle insertions into the mannequin with fat. It should be noted that for these trials, error thresholds of 0.02 N and 0.03 N were also tested to best illustrate the impact of the error threshold setting. A sample set of graphs for one trial from each of the remaining needle and tissue combinations is also included in Appendix B for reference.

As shown in the sample graphs of Figure 10 and Figure 12, the absolute mean error between the modeled force and measured force tends to increase overall as the error threshold of the parameter estimation scheme increases. The exact form and degree of this correlation varies between different cutoff
frequencies used in the analysis for a given trial. In addition, there is considerable variation between not only trials of different insertion tasks, but also between trials of the same insertion task. However, across all data collected, the trend is almost always an increase in model error with an increase in error threshold.

Figure 10: Absolute mean error of modeled force for Trial 2 of 18G catheter needle in the mannequin with fat as a function of (TOP) parameter estimation error threshold and (BOTTOM) normalized filter cutoff frequency
Figure 11: Number of piecewise intervals in force model for Trial 2 of 18G catheter needle in the mannequin with fat as a function of (TOP) parameter estimation error threshold and (BOTTOM) normalized filter cutoff frequency

This is to be expected given the manner in which the parameter estimation scheme splits the model into piecewise intervals. The higher the error threshold is set, the greater the error that is permitted between the modeled force and measured force before the algorithm is triggered to start a new piecewise interval.
As shown in Figures 10 and 12, the absolute mean error of the model tends to decrease exponentially with an increase in the cutoff frequency used to filter the data in the parameter estimation algorithm. Once again, there is some variability in the degree of this trend, but an overall exponential

Figure 12: Absolute mean error of modeled force for Trial 1 of 18G brachytherapy needle in the bovine liver as a function of (TOP) parameter estimation error threshold and (BOTTOM) normalized filter cutoff frequency
Figure 13: Number of piecewise intervals in force model for Trial 1 of 18G brachytherapy needle in bovine liver as a function of (TOP) parameter estimation error threshold and (BOTTOM) normalized filter cutoff frequency.

decrease was observed across all error thresholds for the majority of the trials for each insertion task. At the highest cutoff frequency setting for the low-pass filter, the filtered data is nearly identical to the original measured data. This is due to the fact that the majority of the measured data’s signal spectrum is allowed to pass through the filter, as the cutoff frequency is nearly the Nyquist frequency. However, at the lower cutoff frequencies, the pass band of the filter narrows, allowing only the lowest frequency content of the
measured data to pass. As a result, the filtered force data retains global features of the original measured data, but it does not retain all of the subtle local features. This causes additional error when the model is fit to this filtered data and compared to the original unfiltered data.

Typically, as seen in Figures 10 and 12, the greatest decrease in model error between the low and high cutoff frequencies occurred at an error threshold of 0.01 N, the lowest error threshold tested. As previously mentioned, with a higher cutoff frequency, the filtered data retains more of the local features of the original data. These local features may contain small fluctuations in insertion force, which may be enough to trigger a piecewise segmentation if the error threshold is low enough. However, at a higher error threshold, they may not cause enough of a change in the insertion force to trigger this segmentation. As a result, the model error is more dependent on the cutoff frequency at the lower error thresholds than at the higher error thresholds.

The correlation between the number of piecewise intervals in the model and the parameter estimation error threshold directly opposes the correlation between model error and the error threshold. Across all trials for all insertion tasks, the number of piecewise intervals in the model decreases exponentially as the error threshold is increased. This is demonstrated in Figures 11 and 13. This trend is to be expected, as a higher error threshold means that there must be a greater error between the model and the measured force in order to terminate one piecewise interval and start another in the parameter estimation algorithm. The higher this threshold is set, the less frequent will be the action of ending one piecewise interval and starting another, thus resulting in a smaller number of piecewise intervals.

The effect of the cutoff frequency used in filtering the data on the number of piecewise intervals is highly dependent on the error threshold setting used. As can be seen in Figures 11 and 13, for the lowest error threshold setting used, the number of piecewise intervals increases overall with an increase in cutoff frequency. However, as the error threshold is raised, the magnitude of this overall increase diminishes. At the higher error thresholds, there is no clear correlation between the cutoff frequency and the number of intervals. These trends generally hold across all trials for all insertion tasks tested. As previously
mentioned, when a lower cutoff frequency is used, many of the local features of the original force data are removed in the data used to fit the model. Since these local features are typically only small fluctuations in force magnitude, their presence is unlikely to alter where the error threshold is crossed if the error threshold is set to a higher value. Consequently, if the error threshold is higher, filtering out these features has a negligible impact on the number of piecewise intervals created by the estimation algorithm. However, at a lower error threshold, the magnitude of force fluctuation induced by these local features is enough to cause the error threshold to be crossed. Consequently, at a lower error threshold, whether or not these local features are filtered out directly impacts how many piecewise intervals will be created in the model.

While the trends in the model error and the number of piecewise intervals have been discussed, it is also important to observe the qualitative changes that take place in the modeled insertion force when the parameter estimation algorithm settings are adjusted. Figure 14 shows the effect of increasing the error threshold in the estimation algorithm on the model for Trial 1 of the 18G brachytherapy needle in bovine liver. As the graphs of modeled force overlaid with the measured force show, at an extremely low error threshold, the model captures many of the very slight fluctuations in insertion force. However, it clearly requires many different piecewise intervals to do so, as can be seen by all of the discontinuities in the modeled force. At the higher error threshold, the model only follows the global features of the measured force, neglecting many of the small fluctuations. In doing so, it is clearly modeled with fewer piecewise intervals. This illustrates a key tradeoff between model fidelity and the number of piecewise intervals that will be discussed in more detail in Section 4.1.2.
Figure 14: Modeled and measured force for Trial 1 of 18G brachytherapy needle in bovine liver across different error threshold settings; a cutoff frequency of 0.7 was used for each model.
4.1.2 Selection of Estimation Algorithm Parameters for Further Model Analysis

Section 4.1.1 demonstrates that for both error threshold and filter cutoff frequency settings, there are inherent tradeoffs between the absolute mean error of the model and the number of piecewise intervals. If the error threshold is lowered, the model will have a lower absolute mean error relative to the measured force data, giving it the ability to replicate the measured insertion task with a higher fidelity. However, this increased fidelity comes at the expense of having a greater number of piecewise intervals, bringing with it a greater number of parameters required to model the data. At some point, the number of piecewise intervals will become so high that the number of parameters that must be stored for the model will be greater than the number of measured insertion data points. With so many intervals, it will also be difficult to artificially manipulate the parameters to modify the key haptic cues in the insertion task for training purposes. At such a setting, the utility of the proposed model is lost. Similarly, a higher cutoff frequency setting generally reduces the model error, but, depending on the error threshold setting used, it may also come at the expense of increasing the number of piecewise intervals.

As a result of these tradeoffs, an optimal setting must be found for the parameter estimation algorithm such that an appropriate level of fidelity exists in the model without an excessive number of piecewise intervals. A true optimal setting would be unique to each insertion task, based upon the analysis performed from graphs like those in Figures 10 through 13. In addition, the fidelity required of the model is dependent on the fidelity required in training for a given clinical procedure. For example, training for some procedures may only require the global features of the insertion force be captured by the model, such as the presence of the large peaks in force. In this situation, a larger error may be acceptable in the model. For other procedures, it may necessary for the model to capture some of the smaller fluctuations in force, and thus the acceptable level of error would be lower. The question of how much fidelity in haptic feedback is truly required for effective medical training is still the subject of significant debate [28]. It should also be noted that for some insertion tasks, the magnitude of insertion force is much greater than others. As a result, the acceptable magnitude of error may be higher if the insertion force magnitude is higher. Thus,
when considering the absolute mean error of the model, it is important to consider the magnitude of the error relative to the magnitude of the measured insertion forces.

For the purposes of further studying the model proposed in this paper, an error threshold of 0.04N and cutoff frequency of 0.7 was selected as the optimal parameter estimation setting for all liver insertions. The graphs showing the effects of the error threshold and cutoff frequency, such as Figures 12 and 13, reveal similar trends for both the brachytherapy and conventional hypodermic needles in the bovine liver. Consequently, for simplicity, the settings for both the conventional hypodermic and brachytherapy needles in bovine liver were chosen based upon the optimal setting for just the brachytherapy needle. An examination of the graphs in Figures 12 and 13 reveals how this setting was selected. To demonstrate the utility of the model, it was desirable to have as few piecewise intervals as possible while still maintaining a low model error. It can be seen in Figure 13 that between 0.01N and 0.04N, the number of piecewise intervals decreases nearly threefold across all cutoff frequencies. Beyond 0.04N, the marginal reduction in number of intervals is quite minimal. However, in looking at Figure 12, if the error threshold is increased beyond 0.04N, the model error continues to increase substantially. Therefore, 0.04 N was selected as the error threshold. For selection of cutoff frequency, Figure 13 reveals that the model error may be reduced by increasing the cutoff frequency, but the marginal reduction in error decreases toward the highest frequency. For the lower error thresholds, including 0.04N, Figure 13 also shows that there is no significant change in the number of piecewise intervals as the cutoff frequency is increased. Therefore, a normalized cutoff frequency of 0.7 was chosen.

For the remainder of the insertion tasks, an error threshold of 0.07N and cutoff frequency of 0.7N was selected as the optimal setting. For simplicity in this study, this selection was made using the graphs showing the effects of error threshold and cutoff frequency for the 18G catheter hypodermic needle inserted into the mannequin with fat. The effects of the error threshold and cutoff frequency for this insertion task follow nearly the same trends as the 18G brachytherapy needle inserted into bovine liver. This can be seen in comparing Figures 10 and 11 with Figures 12 and 13. Therefore, nearly the same rationale was used in
selecting the error threshold and cutoff frequency. However, as will be shown in Section 4.2, the magnitude of insertion forces for these insertions is much greater than that of the bovine liver insertions. Consequently, a higher absolute mean model error would likely be acceptable. For this reason, an error threshold of 0.07N was selected instead of 0.04N in order to further reduce the number of piecewise intervals in the resulting models.

4.2 Model Outcomes and Accuracy

With the parameter estimation algorithm set at the optimal error threshold and frequency settings selected from Section 4.1.2, the model parameters and the resulting modeled forces for every trial were used to study the effectiveness of the overall model in replicating insertion force. The absolute mean error over the course of an entire insertion trial was obtained by comparing the modeled force with measured force at each depth. The absolute mean errors for trials of the same insertion task were averaged for comparison. They are displayed by needle and tissue type in Figure 15.

![Bar chart showing average absolute mean error (N) for different needle and tissue types.](chart.png)

Figure 15: Absolute mean error for model over entire insertion averaged by needle and tissue type; +/-1 standard deviation among trials is shown by error bars
Experimentation shows that in all combinations of needle geometries and tissue types tested, except the brachytherapy needle in porcine skin, the average error was below 0.05 N. The higher error of the brachytherapy needle in porcine skin is likely attributable to the much larger magnitude of force measured for the insertion, as can be seen in Figure 19. Similarly, the bovine liver, which saw the smallest insertion force magnitudes, had the smallest average error for both needle types. A simple comparison of absolute mean error across the various needle types reveals that for the data analyzed in this study, there is no clear correlation between needle type and absolute mean model error.

For each combination of needle and tissue tested, a sample insertion trial is shown in Figures 16 through 20. The remainder of the trials are shown in Appendix C. In these figures, the measured insertion forces are overlaid with modeled insertion forces to demonstrate the model’s ability to capture the features of real insertions. When examining these figures, it is important to note that the graphs have varying scales on both axes, and the magnitudes of insertion force may be quite different from one insertion to the next.
Figure 16: Modeled and measured needle insertion force sample for insertion into phantom gel with (TOP) brachytherapy needle and (BOTTOM) conventional hypodermic needle
Figure 17: Modeled and measured needle insertion force sample for insertion into mannequin without fat with (TOP) brachytherapy needle, (MIDDLE) conventional hypodermic needle, and (BOTTOM) catheter hypodermic needle
Figure 18: Modeled and measured needle insertion force sample for insertion into mannequin with fat with (TOP) brachytherapy needle, (MIDDLE) conventional hypodermic needle, and (BOTTOM) catheter hypodermic needle.
Figure 19: Modeled and measured needle insertion force sample for insertion through porcine skin with (TOP) brachytherapy needle and (BOTTOM) conventional hypodermic needle.
4.2.1 Analysis of Model Adaptability to Different Tissue Types

The sample models shown demonstrate the ability of the model to capture key differences between insertions in different tissue types. For needles going through homogeneous tissue, the insertion force is continuous overall and is modeled in only one or two piecewise intervals. However, for needles going through inhomogeneous tissue, the insertion force is highly discontinuous and the model adapts by adding several piecewise intervals to the model to capture all of the major features. When the conventional hypodermic and brachytherapy needles were inserted into the phantom or the mannequin without fat, the tissue encountered was homogeneous. As shown in Figures 16 and 17, there was no initial force peak for
these tissues due to the minimal force required to initially puncture the tissue. In these cases, the force rises in a near linear fashion as friction increases with insertion depth. The increase in friction is due to the increasing contact area between the needle and tissue as more of the needle enters the tissue. As demonstrated by the model’s ability to fit the linear behavior of the homogeneous insertions, the exponential function used in the model can be manipulated to a near linear form for a given range of insertion depth.

When the brachytherapy and conventional hypodermic needles were inserted into the porcine skin, bovine liver, and mannequin with fat, the tissue encountered by the needle was inhomogeneous. This was also the case when the catheter hypodermic needle was inserted into the mannequin with and without fat. Without the fat layer added to the mannequin, the catheter needle was positioned such that it could puncture the mannequin’s artificial artery. This interaction of the catheter needle with this artificial artery is seen in the insertion trial shown in the bottom of Figure 17, where a brief drop in force occurs between an insertion depth of 35 mm and 40 mm. In all of these inhomogeneous tissue insertions, rapid, discontinuous transitions in the force were measured experimentally.

When a layer of excess fat was added to the mannequin, a transition point occurred when the needle exited the fat layer and entered the normal mannequin. This transition can clearly be seen with all three needles in Figure 18 around an insertion depth between 15 and 20 mm. This transition is replicated in the model by splitting the model into several piecewise intervals where there are rapid changes in the slope of the force.

The needle insertions into bovine liver demonstrate the most irregular insertion forces of any of the insertion tasks tested in this study. As can be observed in Figure 20, there are many rapidly developing peaks in the insertion force profile. These peaks correspond to the needle puncturing through the variety of internal structures within the inhomogeneous organ, such as vasculature and connective tissue. As can be seen in the brachytherapy needle insertion, the model is able to typically capture these peaks by splitting each of them into two separate piecewise intervals: one interval for the rise in force and one interval for the rapid release in force. To split them into two intervals, the peaks in the insertion force graph are defined as
critical depths, \( P_n \). In some instances, the release in force is nearly linear, despite the rise in force being nonlinear. The exponential function employed in this model is able to capture both of these behaviors through proper manipulation of the parameter values.

In the conventional hypodermic needle insertions into bovine liver, also shown in Figure 20, the model does not capture any of the features of the insertion profile, but rather models the entire insertion as essentially a single straight line of best fit. The root cause of this occurrence is not a flaw in the model, but rather the use of an improper error threshold in the parameter estimation algorithm. As previously mentioned, the error threshold used for liver insertions was 0.04N, but as shown in Figure 20, the peak forces measured with conventional hypodermic needle were only 0.075N. As a result, the error threshold was never crossed in the parameter estimation algorithm, and a single piecewise interval was fit to the entire insertion force trial. If it were desired to have the model more accurately reflect the features of these conventional hypodermic insertions, the error threshold in the parameter estimation process would simply need to be lowered. In reality, there is likely little utility in doing so from a haptic simulation perspective, as the haptic sensitivity of a person using the simulation would likely prohibit differentiation between a few hundredth Newtons of force.

The needle insertions through porcine skin demonstrate a much different insertion force profile than the other tissue types, primarily due to the fact that the needle was inserted all the way through the porcine skin, which was only a few millimeters thick. In the other insertion tasks, the needle was inserted deep into tissue without puncturing all the way through. Consequently, the insertion force profile recorded for porcine skin insertions only spanned insertion depths of approximately 8 to 15 mm. During insertion through porcine skin, a rapid build-up of force occurs as the needle strains the tissue prior to puncture. The rate at which the force increases in this stage is much greater than the rate of increase observed at any stage of insertion in other tissues. This is due to the high level of stiffness in the porcine skin, which requires a large amount of force to generate the strain at the needle tip needed to puncture through the skin surface. Once the critical strain required for puncture is attained, the needle is able to pierce through the tissue,
resulting in a rapid release of force. Once again, manipulation of the exponential function parameters allow the model to replicate the more rapid increases and decreases in force seen in the porcine skin. The model handles the sharp peak of the insertion force profile by defining the location of the peak as a critical depth, \( P_n \), thereby starting a new piecewise interval as the insertion force decreases.

### 4.2.2 Analysis of Model Adaptability to Different Needle Geometries

The model outputs also demonstrate the ability of the model to capture key differences in insertion force associated with different needle geometries. For the porcine insertions, shown in Figure 19, a rapid rise in force is followed by two distinct releases in force. When enough strain is accumulated in the tissue at the needle tip to puncture the surface, the first release in force occurs. Once the entire bevel has pierced through the thickness of the tissue, the second release occurs. In the insertion of the brachytherapy needle, this first release in force is very subtle, spanning only a fraction of a millimeter. The reduction in force in the first release is also much less than the second. However, for the conventional hypodermic insertion, the first release is much more distinct, spanning several millimeters. The reason for this difference in behavior is that the conventional hypodermic needle has a longer bevel that results in the extended initial release in force as the bevel passes all the way through the tissue. The brachytherapy needle bevel’s shorter length and duller tip require a greater strain in the tissue prior to the initial puncture. This results in a greater initial force build up. Once the critical strain is reach, the brachytherapy needle’s bevel rapidly passes through the tissue, causing a very brief initial release in force that is followed by a much more dramatic second release in force. The difference between the insertions with these two needles is captured in the model by extending the piecewise interval that replicates the first release in force. Modifying parameters within phases also enables replicating the greater peak force, and ensuing greater release in force, observed with the brachytherapy needle.

The duller, shorter bevel of the brachytherapy needle also consistently leads to a greater peak force required to exit the mannequin’s fat layer and enter the normal mannequin. As shown in Figure 18, a
transition in insertion force occurs with all three needles during this event between an insertion depth of about 15 and 20 mm. However, only the brachytherapy needle has a distinct peak followed by a rapid release in force during the transition. For the other two needles, a slight decrease in the slope of the insertion force is observed, but no such sudden release in force. This release in the brachytherapy needle is likely attributable to the higher strain required to either puncture through the back of the fat layer or initially puncture the normal mannequin. The force associated with accumulating such a strain for puncture would be greater than the force of friction and cutting encountered once the surface puncture has just taken place. However, for the other two needles, since a lesser strain is required due to the sharper bevel, the difference between these forces is minimal. Once again, the differences in these behaviors are easily captured in the piecewise intervals of the model.

The model was also able to adapt to the difference in frictional force that exists between the shaft of the brachytherapy needle and the shaft of the conventional hypodermic needle. As previously mentioned, it was observed that the insertion force in homogeneous tissue takes on a linear rise due to the frictional effects of increasing the contact area between the needle and tissue. In both the phantom insertions and mannequin insertions without fat, shown in figures 16 and 17 respectively, the slope of this linear increase is consistently greater for the brachytherapy needle than the conventional hypodermic needle. This indicates that the brachytherapy needle has a greater friction per unit length of needle shaft when inserted into these two tissues. The difference in friction is easily captured in the model through adjustment of the parameters that dictate the slope of the nearly linear piecewise intervals.

4.3 Analysis of Model Error Data

Error was plotted as a function of insertion depth for each trial, as shown in Figures 21 through 25, to gain insight into the model accuracy beyond the absolute mean error values. The sample error plots shown correspond to the insertion trials for which measured and model data is shown in Figures 16 through 20. It is important to note that in order to facilitate easy comparison of the error plots, the scales of both
axes in all graphs are identical. In a few of the insertions, this did result in a portion of the error plot being cut off vertically.

In the homogeneous tissue insertions, which include phantom and mannequin insertions with the brachytherapy and conventional hypodermic needles, one of the largest contributions to model error occurred at the beginning of the insertion. This is shown in Figures 21 and 22. In some cases, the error even resulted in a small negative force to be initially predicted by the model. A likely cause for this error was that in the measured data, the insertion force rose initially in a brief non-linear fashion due to initial deflection of tissue. As friction became the dominant force, the force rise took on a more linear form.

Figure 21: Model error versus insertion depth for needle insertion into phantom gel for (TOP) brachytherapy needle and (BOTTOM) conventional hypodermic needle
Figure 22: Model error versus insertion depth for needle insertion into mannequin without fat for (TOP) brachytherapy needle, (MIDDLE) conventional hypodermic needle, and (BOTTOM) catheter hypodermic needle.
Figure 23: Model error versus insertion depth for needle insertion into mannequin with fat for (TOP) brachytherapy needle, (MIDDLE) conventional hypodermic needle, and (BOTTOM) catheter hypodermic needle.
transition between these behaviors was rather smooth, and consequently the error threshold was never crossed in the parameter estimation algorithm. With the error threshold never crossed, only one piecewise interval was assigned to model both of these behaviors. This resulted in an error at the very beginning of the insertion where the force was briefly more non-linear. In future modeling, this could be addressed by assigning a separate piecewise interval to the initial non-linear portion by lowering the error threshold of the parameter estimation algorithm. However, it should be noted that this may come at the expense of adding additional piecewise intervals elsewhere as well.

Figure 24: Model error versus insertion depth for needle insertion into porcine skin for (TOP) brachytherapy needle and (BOTTOM) conventional hypodermic needle
Figure 25: Model error versus insertion depth for needle insertion into bovine liver for (TOP) brachytherapy needle and (BOTTOM) conventional hypodermic needle

In comparing the error plots of the insertions into the animal tissue with the insertions into the artificial tissue, the error appears to fluctuate much more rapidly with position in the animal tissue and have a noisier appearance. These rapid fluctuations in error can be attributed to the rapid fluctuations in insertion force that occur in the animal tissue. The inhomogeneous nature of the animal tissue, compared to the uniform, homogeneous nature of artificial tissue, causes these rapid fluctuations. As non-uniformly distributed anatomical substructures are deflected, cut, or punctured, the insertion force changes quite rapidly. In an artificial tissue, the insertion force is much more stable, steadily increasing as friction increases with needle contact area. The exception in this behavior for artificial tissue occurs when the needle
interacts with the artificial anatomical features of the mannequin, such as the extra fat layer or the artery. In these interactions, a rapid fluctuation in force does occur, but it only occurs for a limited insertion length. Once the needle has passed through the feature, it once again is cutting through homogeneous synthetic tissue, allowing insertion force to stabilize. This is a stark contrast with real animal tissue, where the entire tissue is inhomogeneous due to the random distribution of anatomical structures like connective tissue and vasculature.

In comparing the error plot in Figure 25 for brachytherapy needle insertion into bovine liver with corresponding measured and modeled data in Figure 20, it can be seen that major error spikes correspond to the large force peaks within the measured data. It can be visually observed in Figure 20 that the model appears to predict the magnitude of these force peaks quite accurately. However, the position at which these peaks occur is shifted very slightly from the true position resulting in a brief significant error when the model is compared with the measured data. These miniscule shifts in position of the force peaks would likely have a negligible impact when it comes to using the model for haptic simulation. A similar occurrence can be found in the brachytherapy needle insertion into porcine skin shown in Figure 19. Following the largest force peak, the rapid release in force predicted by the model is shifted slightly from the measured release in force. If it was desired to remove the occurrence of these shifts, one could increase the filter cutoff frequency in the parameter estimation algorithm and lower the error threshold. However, doing so would add several piecewise intervals to the model, reducing its overall simplicity.

The acceptable level of error in the force model is a question of the fidelity required in the overall simulation system. There is still significant debate as to what level of fidelity is truly necessary to provide effective medical training, particularly considering the cost trade-offs associated with attempting to increase fidelity [28]. As previously mentioned, error can be further reduced by segmenting measured force data into much smaller sections. This can be accomplished by lowering the error threshold of the parameter estimation algorithm. However, in doing so, the utility of the parameterization scheme is lost. The key advantage of this model is that it provides a simple framework for a variety of clinical scenarios to capture
and manipulate the major haptic cues that occur along the axis of a needle as it progresses on a one dimensional insertion path.

4.4 Demonstration of Using Model to Synthetically Create Insertion Force

Thus far, the primary focus of this work has been placed on determining whether the proposed mathematical model is capable of modeling needle insertion forces. The ability of the proposed model to be adapted to a variety of needle insertion tasks has been demonstrated. Through parameter manipulation, the model has been shown to be capable of replicating an insertion force profile as simple as an insertion into homogeneous phantom gel and as complex as insertion into bovine liver. However, so far, the parameters used to create these models have been obtained using real data in conjunction with the automatic parameter estimation algorithm developed in Section 2.2. In this section, a key utility of the model will be demonstrated: the ability to synthetically create an insertion force profile and manipulate model parameters to make deliberate changes representative of clinical variability in tissue.

To demonstrate the ability to synthetically generate and manipulate an insertion force profile using the model, the insertion forces of a conventional hypodermic needle through porcine skin were replicated. As shown in the sample measured insertion force profile in Figure 26, the profile for this insertion task generally is comprised of a single build up in force followed by two distinct releases in force. First, the general form of the measured insertion profile was replicated using the model parameters listed in Figure 27. These parameters were determined iteratively through a simple trial and error process. When applied to the model, the parameters yield the insertion force profile shown in Figure 27, which is very similar to the measured insertion force profile shown in Figure 26.

As previously mentioned, the first release in force in the porcine skin insertions corresponds to the bevel having first punctured the tissue surface. The first release ends once the entire bevel has cut through the thickness of the tissue. In a thicker tissue sample, this first release in force would likely span a
longer insertion length, as there would be more tissue for the bevel to cut through. To simulate a thicker skin sample being punctured, the model may be manipulated, as shown in Figure 28, to extend the piecewise interval that contains this first release in force. The parameters altered to allow this modification are highlighted in yellow in the table shown in the figure. One of the key adjustments includes increasing the
values of $P_3$ and $P_4$ to account for the larger third interval. Previously, this interval spanned 3.35 mm, but with the parameter change to simulate thicker tissue, it was modified to span 4.6 mm.

In addition to variation in tissue thickness, it may be desirable to adjust the model to account for variations in tissue stiffness, such as those that may be caused by natural biological variation or by a specific pathological condition. An increase in tissue stiffness requires that there be a greater force exerted by the needle tip in order to achieve the local tissue strain required for needle puncture. Consequently, the peak force of the insertion profile would be higher in a stiffer tissue, and the rate at which force initially increases with needle insertion depth would also be greater. The rate at which the force decreases after puncture would be greater as well because there would be a larger force applied to the needle at the moment it punctures the surface of the tissue. The increased force applied to the needle would also enable it to cut through the tissue faster, likely resulting in a decrease in the length of the first release in force. The parameters from the original model in Figure 27 were adjusted as shown in Figure 29 to successfully make these modifications to the insertion force model. The resulting model of insertion into a stiffer tissue sample is shown in the graph in Figure 29.

Figures 27 through 29 demonstrate the ability to synthetically recreate a real insertion force profile and manipulate it to account for tissue variability. However, the small, irregular fluctuations in insertion force that occur in the measured data are not reflected in the model. Instead, the model simply captures the overall trends of the insertion forces in a manner that results in a smoothed insertion force profile. While it is unlikely that these minor fluctuations serve as significant haptic cues to a physician when performing an insertion procedure, including them may add a certain degree of realism if the model were to be used for simulation. In Section 4.3, it was discussed how error plots were obtained by finding the error between the modeled and measured insertion forces at each insertion depth. The error data obtained during this process for the insertion trial shown in Figure 26 was arbitrarily added to the modeled insertion force for stiff tissue in Figure 29. The resulting modeled insertion force is shown in Figure 30, and it appears to have a significant degree of added realism. In this case, the error obtained from an earlier model provided an
approximation of how the real insertion force in porcine tissue fluctuates slightly from the overall trend. If a simple function were created to replicate the magnitude and frequency of these fluctuations, the fluctuations could be arbitrarily added to any model to achieve additional realism if desired.

![Figure 28: (LEFT) Modified model parameters used to replicate conventional hypodermic needle insertion through thicker porcine skin and (RIGHT) resulting modeled insertion force; The parameters modified to simulate the thicker tissue are highlighted in yellow](image)

![Figure 29: (LEFT) Modified model parameters used to replicate conventional hypodermic needle insertion through stiffer porcine skin and (RIGHT) resulting modeled insertion force; The parameters modified to simulate the stiffer tissue are highlighted in yellow](image)
Figure 30: Modeled insertion force from Figure 29 with model error added to simulate the small fluctuations in insertion force observed in real tissue.
Chapter 5

Conclusion

5.1 Summary and Conclusions from This Work

A dynamic model has been presented for modeling axial needle insertion force as a function of insertion depth without many of the drawbacks associated with the complexity of other methods: namely detailed mechanical approximations, required determination of mechanical properties, and high computational demand. In the proposed model, needle insertion force is modeled in a piecewise manner using a series of exponential functions each consisting of four parameters. By adding, removing, and shifting piecewise intervals, in addition to modifying the parameters of the function within each interval, the model can replicate a variety of insertion tasks and clinical scenarios.

The ability of the model to replicate insertion forces from a variety of needles and tissue samples was validated through experimentation. A MATLAB-based algorithm was developed to automatically take measured insertion force versus position data and determine the model parameters that would allow the model to replicate the data. Two key settings within this algorithm allowed some degree of control over the magnitude of error and the number of piecewise intervals in the resulting model. It was found that overall, reducing the error came at the expense of increasing the number of piecewise intervals, which added complexity to the model. A method for optimizing these settings was outlined and used to select settings to be used for further model analysis. With the MATLAB-based-algorithm developed, controlled laboratory needle insertion experiments were conducted in which the insertion force versus position was measured for 12 different combinations of needle and tissue types. The MATLAB algorithm was then used to determine the model parameters for each insertion trial, which allowed generation of modeled forces replicating each insertion trial. The modeled forces replicated the measured forces with a low average absolute mean error,
less than 0.05 N in 11 of 12 combinations of needle and tissue tested. In addition, qualitative analysis revealed that the model was able to capture the key features of the insertion force profile that differ between tissue types and needle geometries. Analysis of the error between the modeled and the measured insertion forces as a function insertion depth revealed that some of the larger contributors to model error could be reduced by adding additional piecewise intervals. It was also found that the error for real animal tissue fluctuated much more rapidly with position than that of artificial tissue due to the presence of randomly distributed inhomogeneities. Some of this rapid error fluctuation was due to misalignment of the insertion force peaks in the model with the measured peaks; however, this would likely have negligible impact on using the model for simulation purposes.

The ability to deliberately manipulate model parameters to simulate desired clinical variation in tissue was also demonstrated. Parameters were selected through trial and error that would replicate a real insertion into porcine tissue. Through parameter modification, the resulting model was successfully altered to simulate a thicker tissue sample and a stiffer tissue sample. In addition, a method was presented for adding realism into the model by leveraging previously captured model error data to add random fluctuations to the insertion force.

5.1 Directions of Future Work

The future goal of this work is to implement this modeling scheme into a low cost, low fidelity simulation system that can be used in training multiple needle insertion procedures. Through manipulating the model parameters as was done in Section 4.4, specific elements of clinical variability may be targeted for training within a given insertion procedure. Thus, the potential utility of this model is two-fold: simplicity in being able to adapt to train different insertion procedures and the ability to provide enhanced training through manipulation of specific features of insertion forces.

Prior to implementing the model in a simulation system, the velocity dependence of model parameters must be studied and incorporated into the model to provide additional realism to simulations.
Experimental data will also need to be obtained for true clinical insertion procedures in order to establish the proper parameter values and provide a framework to modify the parameters to simulate clinical variability. Lastly, if a true utility is found in incorporating the small, random insertion force fluctuations of real tissue, a function should be developed that replicates the magnitude and frequency of model error fluctuations found in section 4.3.
Appendix A

Parameter Estimation Algorithm MATLAB Code

1) `function [ non_lin_coeff, crit_points_Final, y, time ] = Tissue_Fit_Final(pos, force, threshold, filt_freq, filt_order, Deriv_Thresh)`

2) `tic %starts timer`

3) `%% FITTING EACH SECTION OF THE LINE`

4) `[F,G]=butter(filt_order,filt_freq); %Defines filter parameters`

5) `force=filter(F,G,force); %Applies Butterworth filter to force data`

6) `safety=0 %Safety =1 indicates that the most recent segmentation of the was model due to crossing the error threshold`

7) `N=4 %the algorithm will fit an additional four data points at a time if the error threshold has not been crossed`

8) `j=5; %Defines array position of the positional data point through which the model is being fit`

9) `sh=0; %Variable used to ensure convergence in curve fit`

10) `count=0 %Counter used for diagnostic of logic condition line 61`

11) `error=0; %Starts current error at 0`

12) `z=1; %Defines array position of beginning of the positional data range through which the model is being fit`

13) `Deriv=0 %Starts first derivative variable at 0`

14) `c=3 %Counter used for diagnostic of logic condition in line 48`

15) `i=0 %Counter for while loop line 32`

16) `k=0 %Defines array element position of critical points`

17) `crit_points(1)=1 %Initial critical points`

18) `crit_points_Final(1)=1 %Corrected critical points`

19) `while j<=length(force) %Prevents code from running beyond data range`

20) `i=0 %reset loop counter for line 32 at 0`

21) `k=k+1`

22) `transition=0; %Reset transition condition to 0`

23) `Deriv1=0; %Reset reference derivative to 0 at reset of while loop`

24) `while abs(error)<=threshold && j<=length(force)&&transition==0` %Loop only runs if model hasn't exceeded error threshold, j hasn't exceeded data range, and the transition condition is 0

25) `i=i+1;`

26) `range=z:j; %sets range for which curve fit will take place`

27) `g= fittype('a.*exp(b.*(x-d))+c'); %defines equation to be fit`

28) `f = fit(pos(range),force(range),g,'StartPoint',[0,0,0,0],'Upper',[inf, inf, inf, sh+.0001], 'Lower',[-1*inf,-1*inf,-1*inf, sh-.0001]); %fits equation to data; start point in numerical fit defined as {0 0 0 0} in order to ensure convergence consistently, upper and lower bounds for variable d are limited such that d is equal to the previous critical point`
30)  non_lin_coeff(:,k)=(coeffvalues(f))'; %store coefficient values for current segment

31)  phase_coeff=non_lin_coeff(:,k);
32)  y(range)=phase_coeff(1).*exp(phase_coeff(2).* (pos(range)-phase_coeff(4)))+phase_coeff(3); %generates model force outputs based upon curve fit

33)  error=y(j)-force(j); %calculates error between most recent force data point and model predicted force at that point

34)  %plot(pos(1:j),y(1:j),pos(1:j),force(1:j)) %optional plot feature to see fitting in real time

35)  Deriv=(y(j)-y(j-N))./(pos(j)-pos(j-N)); %approximates derivative over the previous four data points

36)  if i==2
37)  Deriv1=(y(j)-y(j-N))./(pos(j)-pos(j-N)); %stores first derivative of second loop cycle as the reference derivative
38)  else
39)  end
40)  if abs(Deriv)<abs(Deriv*Thresh*Deriv1) && Deriv<0 && safety==1 %checks if the current derivative is less than the given threshold relative to the reference derivative,
41)  %checks that the derivative is negative, checks that the derivative threshold is not being crossed immediately following a previous crossing
42)  c=c+1
43)  transition=1;
44)  safety=0 %used to indicate that derivative threshold was just crossed to cause most recent segmentation of model
45)  else
46)  transition=0;
47)  end
48)  j=j+N; %advances to the next data point by four
49)  end
50)  if transition==0 %ensures that the fitting process does not continue in the event a derivative threshold is crossed
51)  j=j-2*N; %algorithm goes back to the beginning four data points where the error threshold was crossed

52)  if z>j %ensures that if the error threshold is crossed on the first run of the above while loop, that the section will have its own model segment
53)  j=j+4;
54)  count=count+1
55)  else
56)  end
57)  error=0; %reset error threshold 

58)  %line 81 through 92 works fits the data in the same manner, but 
only advances by one points at a time 

59)  while abs(error)<=threshold && j<=length(force) 

60)  range=z:j; 

61)  f = 
fit(pos(range),force(range),g,'StartPoint',[0,0,0,0],'Upper',[inf, inf, inf, sh+.00001],'Lower',[-1*inf,-1*inf,-1*inf, sh-.00001]);%start point 
defined as [0 0 0 0] in order to ensure convergence consistently;may 
need to be altered to other values 

62)  non_lin_coeff(:,k)=(coeffvalues(f))';%%store coefficient values 
for non-linear segment 

63)  phase_coeff=non_lin_coeff(:,k); 

64)  y(range)=phase_coeff(1).*exp(phase_coeff(2).*(pos(range)- 
phase_coeff(4)))+phase_coeff(3); 

65)  error=y(j)-force(j); 

66)  %plot(pos(1:j),y(1:j),pos(1:j),force(1:j)) 

67)  j=j+1; 

68)  end 

69)  safety=1; %used to indicate that the most recent segmentation was 
due to error threshold crossing 

70)  else 

71)  j=j+1; %if the derivative threshold was crossed, this advances 
the j variable 

72)  j=j-N %to the correct position to be compatible with the 
remaining code 

73)  end 

74)  p=2; 

75)  crit_points(k)=j-p; %defines critical point as the one prior to 
the error threshold or derivative threshold being crossed 

76)  z=j-p; %defines beginning of fit range as the critical point 

77)  j=j+1; %advances j variable to allow the next segment to be fit 

78)  if j<=length(force) 

79)  sh=pos(crit_points(k)); %defines sh variable to be equal to the 
critical point 

80)  error=0; %resets error at 0 

81)  else 

82)  end 

83)  end 

84)  % FIND INTERSECTION BETWEEN ADJACENT MODEL SEGMENT EQUATIONS--
REDEFINE CRITICAL POINTS TO BE THESE INTERSECTIONS 

85)  if numel(crit_points)>1 %Checks if there has been more than one 
critical point found 

86)  for k=1:length(crit_points)
if k==length(crit_points) % do not want to include critical point because it does not mark the intersection of two segments

else % for all critical points except for last one

u=@(x)non_lin_coeff(1,k).*exp(non_lin_coeff(2,k).*(x-
non_lin_coeff(4,k)))+non_lin_coeff(3,k)-
(non_lin_coeff(1,k+1).*exp(non_lin_coeff(2,k+1).*(x-
non_lin_coeff(4,k+1)))+non_lin_coeff(3,k+1)); % find intersection between adjacent exponential and linear phases based on model fits, sets exponential model equation = linear model equation, coefficients from each respective phase applied, solving for symbolic variable x

intsct(k)=fsolve(u,pos(crit_points(k))) % solves for intersection between adjacent segments

end

end

for k=1:(length(crit_points)-1) % don't want to change final critical point because it is not at an intersection of two segments

diff=abs((pos)-intsct(k)); % find the difference in absolute value between the critical point and every position coordinate

[mins,loc]=min(diff); % find closest position coordinate to the intersection point and its array position in the pos vector

crit_points_Final(k)=pos(loc); % change critical point from the original critical point to the position coordinate nearest to the intersection between the model-fit segments

if k>1 % include every critical point except first one

if crit_points_Final(k)<=crit_points_Final(k-1) ||
crit_points_Final(k)>=pos(crit_points(k+1)) % check to make sure the new critical point is not before or after adjacent original critical points

crit_points_Final(k)=pos(crit_points(k)) % changes critical point to be the original location

else

end

else

end

end

if numel(crit_points_Final) ~= 1 % checks if there are more than one critical points

crit_points_Final(numel(crit_points_Final)+1)=pos(end); % makes final critical point equal to the final position data point

elseif crit_points_Final(1)~=1 % checks if any critical points have been found

crit_points_Final(numel(crit_points_Final)+1)=pos(end);

else % if no critical points have been found

crit_points_Final=pos(end);

end

end

end

end

%% APPLYING COEFFICIENTS TO GENERATE OUTPUT OF FITTED FUNCTION
for k=1:length(crit_points_Final) %cycles through all segments
if k==1 %checks if current critical point is the first one
   i=1; %defines array position in 'pos' of low end value of position range (first data point for first phase)
else %all other phases
   i=find(pos==crit_points_Final(k-1)); %defines 'pos' array position of low end value of position range using previous critical point
end

range=(i:find(pos==crit_points_Final(k))); %extracts position range for current phase using critical points

phase_coeff=non_lin_coeff(:,k); %applies model coefficients to data over current segment range to generate model output

end

y=y'; %transpose model output to vertical vector

58) time=toc %stop ti
Appendix B

Plots Showing Effect of Error Threshold and Cutoff Frequency in Parameter Estimation Algorithm

Trial 1, Catheter hypodermic needle inserted into mannequin with fat
Trial 2, Catheter hypodermic needle inserted into mannequin with fat
Trial 3, Catheter hypodermic needle inserted into mannequin with fat
Trial 4, Catheter hypodermic needle inserted into mannequin with fat

![Graphs showing model absolute mean error and number of model piecewise intervals against error threshold and normalized cutoff frequency.](image-url)
Trial 5, Catheter hypodermic needle inserted into mannequin with fat
Trial 1, Brachytherapy needle inserted into bovine liver
Trial 2, Brachytherapy needle inserted into bovine liver

Diagram showing the relationship between Model Absolute Mean Error (N) and Error Threshold (N) for different values of Normalized Cutoff Frequency. The number of Model Piecewise Intervals is also plotted against Error Threshold (N) for the same range of Normalized Cutoff Frequency values.
Trial 3, Brachytherapy needle inserted into bovine liver
Trial 4, Brachytherapy needle inserted into bovine liver
Trial 5, Brachytherapy needle inserted into bovine liver

Normalized Cutoff Frequency

Model Absolute Mean Error (N)

Number of Model Piecewise Intervals

Error Threshold (N)

Normalized Cutoff Frequency

Error Threshold (N)

Normalized Cutoff Frequency

Error Threshold (N)
Trial 1, Conventional hypodermic insertion into bovine liver
Trial 1, Conventional hypodermic insertion into mannequin without fat

![Graphs showing error thresholds and normalized cutoff frequencies vs. model absolute mean error and number of model piecewise intervals.](image_url)
Trial 1, Catheter hypodermic insertion into mannequin without fat

![Graphs showing the relationship between Model Absolute Mean Error (N) and Error Threshold (N) for different normalized cutoff frequencies and piecewise intervals.](image)
Trial 1, Brachytherapy needle insertion into mannequin without fat
Trial 1, Conventional hypodermic insertion into mannequin with fat

![Graphs showing model absolute mean error and number of model piecewise intervals vs. error threshold and normalized cutoff frequency.](image-url)
Trial 1, Brachytherapy needle insertion into mannequin with fat
Trial 1, Conventional hypodermic insertion through porcine skin:

- Model Absolute Mean Error (N)
- Number of Model Piecewise Intervals
- Normalized Cutoff Frequency

- Error Threshold (N)
- Error Threshold (N)
- Error Threshold (N)
- Error Threshold (N)

- Model Absolute Mean Error (N)
- Number of Model Piecewise Intervals
- Normalized Cutoff Frequency

- Error Threshold (N)
- Error Threshold (N)
- Error Threshold (N)
- Error Threshold (N)
Trial 1, Brachytherapy needle insertion through porcine skin:
Trial 1, Conventional hypodermic insertion into phantom gel
Trial 1, Brachytherapy needle insertion into phantom gel

![Graphs showing Model Absolute Mean Error (N) vs. Error Threshold (N) and Number of Model Piecewise Intervals vs. Error Threshold (N) for different Normalized Cutoff Frequencies and Error Thresholds.](image-url)
Appendix C

Measured and Modeled Insertion Force for All Trials

Brachytherapy needle insertion into bovine liver:

Trial 2

Trial 3

Trial 4

Trial 5
Conventional hypodermic insertion into bovine liver:

Trial 1

Trial 2

Trial 3

Trial 4

Trial 5
Conventional hypodermic insertion into mannequin without fat:

Trial 1

Trial 2

Trial 3

Trial 4

Trial 5
Catheter hypodermic insertion into mannequin without fat:

Trial 1

Trial 2

Trial 3

Trial 4

Trial 5
Brachytherapy needle insertion into mannequin without fat:

Trial 1

Trial 2

Trial 3

Trial 4

Trial 5
Conventional hypodermic insertion into mannequin with fat:

Trial 1

Trial 2

Trial 3

Trial 4

Trial 5
Catheter hypodermic insertion into mannequin with fat:

Trial 1

Trial 2

Trial 3

Trial 4

Trial 5
Brachytherapy needle insertion into mannequin with fat:

Trial 1

Trial 2

Trial 3

Trial 4

Trial 5
Brachytherapy needle insertion through porcine skin:

Trial 1

Trial 2

Trial 3

Trial 4

Trial 5
Conventional hypodermic insertion through porcine skin:

Trial 1

Trial 2

Trial 3

Trial 4

Trial 5
Brachytherapy needle insertion into phantom gel:

Trial 1

Trial 2

Trial 3

Trial 4

Trial 5
Conventional hypodermic insertion into phantom gel:

Trial 1

Trial 2

Trial 3

Trial 4

Trial 5
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EDUCATION
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WORK EXPERIENCE
Siemens Infrastructure & Cities
Engineering Leadership Development Program Intern, Low and Medium Voltage
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- Participated in the design of new line of circuit breakers as product development team member
- Built, tested, and evaluated several breaker current path designs for UL thermal calibration potential
- Used ProE to redesign external safety locking mechanism to accommodate other design changes

GE Healthcare
Operations Management Leadership Program Intern-Manufacturing Engineering
Salt Lake City, UT
- Analyzed, redesigned, and implemented improvements to FDA regulatory labeling process for C-Arm X-Ray machines in response to a Corrective and Preventative Action (CAPA) assigned to the previously error-prone process
- Collaborated with several manufacturing engineers to synthesize multiple ideas and designs into a single semi-automated process with comprehensive improvements
- Saved $127K/year through 50% reduction in process cycle time and 92% reduction in errors

Precision Medical Instrument Design Lab,
Penn State Department of Mechanical Engineering
Research Assistant
- Developing empirical model of surgical needle insertion force that can replicate the response of different tissue types and conditions for undergraduate honors thesis
- Modeling work is part of interdisciplinary project to develop improved catheter insertion training device
- First author on paper related to thesis work accepted to ASME MSEC conference

LEADERSHIP EXPERIENCE
Schreyer Honors College
Orientation Mentor
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- Helped organize and run program to acclimate students to the Honors College and its opportunities

Bridges to Prosperity, Penn State Chapter
Chapter Officer
University Park, PA
- Organized and helped lead club to establishment as chapter of international organization that designs and constructs bridges in impoverished communities across the globe
- Created fundraising and marketing materials for chapter's first bridge; recruited new members

Congressional Day Camp
Sports Counselor
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- Planned and led daily sports activities for young campers while supervising the safety of children

ACTIVITIES
Penn State Intramural Soccer, Football, and Basketball
Penn State Engineers Without Borders
Woodson High School Varsity Soccer (Team Captain)

AWARDS
Penn State Evan Pugh Scholar Award
Department of Mechanical and Nuclear Engineering Wharton Scholarship
Tau Beta Pi Engineering Honor Society
National Merit Commended Student