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PRINCIPAL INVESTIGATOR: Aaron Young

CONTRACTING ORGANIZATION: Georgia Institute of Technology
Atlanta, GA 30332

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Aaron Young

Krishan Bhakta

E-Mail: aaron.young@me.gatech.edu

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14. ABSTRACT
This research will develop intuitive and smart intent recognition systems for powered prostheses to predict user intent to optimally supply power to the gait cycle during locomotion tasks. Intelligent intent recognition systems are needed for these prostheses to be clinically deployable. The primary scope of this project first involves developing and preparing a powered prosthesis complete with control technologies for clinical testing with patients with transfemoral amputation. We will collect data during walking which includes various speeds, stairs and ramps. We will compare the clinical effectiveness of different intent recognition systems on lower limb amputees using a powered prosthesis. This research will result in clinically meaningful parameters including the success rate, speed and energetic cost of the amputees performing a circuit of locomotion activities including level walking, stairs and ramps. Biomechanics of movement and energetic cost using the controllers will be quantified and compared to passive prosthesis ambulation. Results to date include the improved development of the mechanical, electrical, and control systems for the powered prosthesis. We have performed tuning and data collection on 9 subjects. This data has gone into the refinement of machine learning algorithms for seamlessly and continuously estimating walking speed and ground slope to improve community ambulation. Results show the relative ease of using our controllers as well as showing improved functionality in different ambulation compared to their conventional passive prostheses.

15. SUBJECT TERMS: Powered knee/ankle prostheses, amputation, intent recognition, biomechanical outcomes, prosthetic control systems, pattern recognition

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1. INTRODUCTION:

Powered prostheses are a promising new technology that may help lower limb amputees to function at higher levels in their daily lives. These individuals suffer from significantly impaired mobility including expending up to 60% more energy than non-amputee individuals. Less than 25% of transfemoral amputees older than 50 achieve community mobility on passive prostheses. Research and industry teams have begun building powered prostheses that include motors to actively assist amputees to walk and perform various tasks encountered in everyday situations such as stepping up a stair, standing up, and traversing difficult and uneven terrain such as slopes and ramps. An important objective is for the computer on the prosthesis to understand what the amputee wants to do. By accurately decoding the amputee's intentions, the computer can appropriately coordinate the assistance of the powered prosthesis to the amputee's needs. A powerful technique to understand the amputee's intentions is to use pattern recognition, which is a technology that is commonly used in speech recognition, image analysis and medical diagnostics. Pattern recognition is capable of automatically determining the amputee's intent and can allow amputees to easily and intuitively use their powered prostheses in their everyday lives. However, if the pattern recognition software incorrectly estimates the user intent, then the powered prosthesis may not be as helpful or may even get in the way of an amputee's intended movements. Additionally, pattern recognition requires training data that must be collected from the amputee before using it. We have developed new pattern recognition systems that are more accurate and do not necessarily require training data directly from the amputee. The proposed research will develop and test these pattern recognition systems with amputees using a state-of-the-art powered prosthesis. The research will determine the benefit of pattern recognition intent recognition systems by measuring key clinical parameters such as how quickly amputees are able to move with the powered prosthesis and their energetic cost of doing so. The end result of this research will be intent recognition systems capable of implementation on computers embedded on powered prostheses. This will be useful to lower limb amputees who use powered prostheses in the future as intent recognition systems can help amputees achieve a greater level of independence and mobility.

2. KEYWORDS:

Powered knee/ankle prostheses, amputation, intent recognition, biomechanical outcomes, prosthetic control systems, pattern recognition

3. ACCOMPLISHMENTS:

What were the major goals of the project?

Specific Aims 1: **Compare intent recognition accuracy of the user-independent system to the user-dependent system in real-time as amputees ambulate over different locomotion modes.**

Major Task 1: Subject Recruitment and Fitting

- Milestone of HRPO and IRB approval at 3 months – 100% completion (on time)

Major Task 2: Prepare prosthetic leg for amputee testing

- Milestone of fully functional system ready for patient testing at 9 months – 100% complete (on time)

Major Task 3: Amputee training and initial data collection for pattern recognition systems

- Milestone of a full set of data from each subject collected at 18 months – 45% complete

Major Task 4: System Implementation

- Milestone of user-dependent and user-independent intent recognition systems ready for deployment – 25% complete

Specific Aim 2: **Quantify the metabolic cost of walking, amputee biomechanics of motion and completion time and compare between user-dependent and user-independent intent recognition**

Major Task 5: Comparison of user-dependent and user-independent systems during a real-time experiment

- Milestone – experimental comparison between clinical effectiveness of different intent recognition controllers on amputees – 0% complete

Specific Aim 3: **Compare clinical outcome measures of powered prosthesis ambulation with active intent recognition to passive prosthesis ambulation.**

Major Task 6: Comparison of clinical parameters of powered prosthesis compared to passive prosthesis

- Milestone – experimental comparison of clinical effectiveness of powered prosthesis compared to passive prosthesis – 25% complete

What was accomplished under these goals?

Quarter 1 Activities and Accomplishments:

Major Task 2: Prepare prosthetic leg for amputee testing

We have been continually working to make improvements to our overall system even though patient testing started around month 9 of the grant. In January and February, we designed a way of getting the Li-Po battery to be onboard the device for ease of testing, reducing safety concerns, and lowering the time for experimental setup (See Figure 3 and 4). Other mechanical improvements to the device included creating better straps for able-bodied walking adapter to ensure the interface would not get loose over time as an experimental protocol was being run. Nylon feet were manufactured for both left and right sided amputations to allow for the user to feel more comfortable walking with the device. New torsional springs were manufactured with the same design except with a smaller thickness to reduce the stiffness to allow for better closed loop control. Additional heights to adjust to a wider range of transfemoral amputees were machined for the prosthesis shank insert.

Major Task 3: Amputee training and initial data collection for pattern recognition systems

In January, testing with able-bodied subjects was a priority to ensure stability of the device across walking speeds. A metabolic system was used to measure energy expenditure across the different conditions in order to get a baseline to compare with. Subjects were first asked to walk in parallel bars and then told to walk over the treadmill at variable speeds. In February, the controls architecture was expanded to have the functionality of performing different ambulation modes (level-walking, ramp ascent/descent, and stair ascent/descent). This allows for the operator to easily change ambulation modes directly from the GUI while an experiment is being performed. Another important addition to the control framework was to add the ability to scale equations on impedance parameters easily from the GUI compared to changing values in the actual code and re-compiling which may take some time and hinder experimental protocols. Both of these additions were important to develop since they would allow users to ambulate better in a more natural and smooth manner. In March, we also began testing our new control framework by tuning parameters for ramp ascent for both an able-bodied subject and a patient with transfemoral amputation (Figure 5). Several trials were tested both on a treadmill that had an ability to adjust inclination angle as well as walking up a ramp on our terrain park at different grades.

Over the course of the last few months, we were able to collect more data with both able-bodied subjects and amputee subjects (~25 sessions with able-bodied subjects and ~7 sessions with amputees). In order to begin creating our intent recognition system, we had 2 amputees walking at a range of speeds from .63 m/s to 1.07 m/s on a level-ground treadmill (Figure 4). We found that we were able to achieve excellent kinematic results and maintain comfortable walking across the wide range of walking speeds for both subjects (Figures 1 and 2). We began exploring different machine learning algorithms that could estimate walking speed with the embedded mechanical sensors on the device which includes encoders, IMU's, and a 6-DOF load cell. Different classification and regression techniques were primarily explored since there is not a single-best approach that is best suited for estimating walking speed. We plan to be able to use these machine learning techniques in real-time with our device, where the algorithm can make informed decisions based off of a trained model. Another experimental procedure that was tested with able-bodied subjects included scaling an equation based on walking speed. We wanted to compare how well the equation could adapt to walking speeds under different trajectories. Specifically we started by scaling the stiffness impedance parameter in late stance to be adjusted by an equation that linearly scales in accordance to walking speed. In order to keep developing the hardware and real-time implementation of machine learning for our intent recognition system, different microcontrollers were benchtop tested to see how all of our sensors would be integrated into the new system.

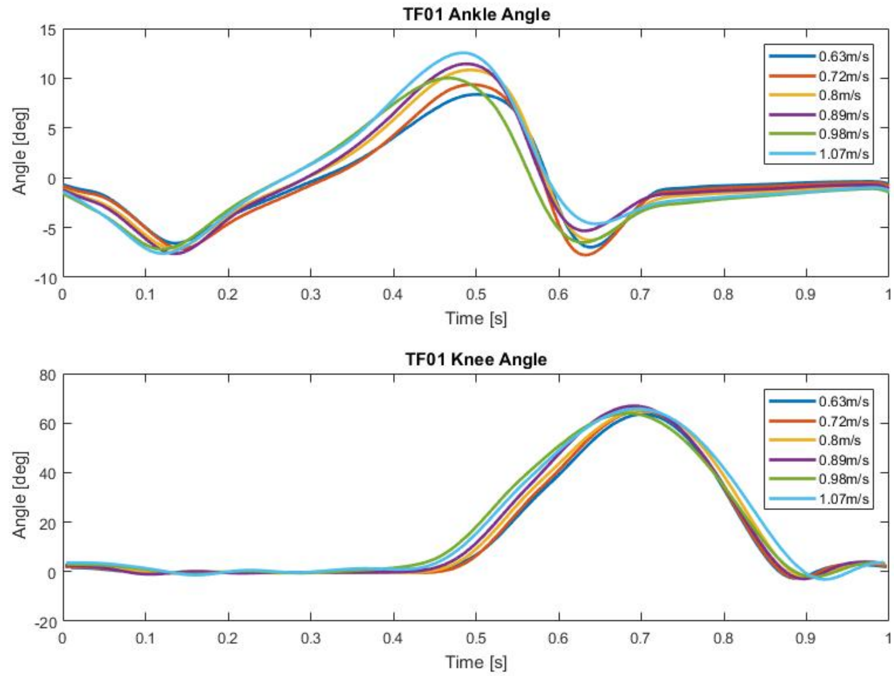


Figure 1: Prosthesis kinematics as a function of walking speed for the first transfemoral amputee subject. Importantly, we are able to maintain similar kinematic profiles at both the knee and ankle across a wide range of walking speeds. We did not need to change underlying impedance parameters across conditions, thus showing our controller was able to easily accommodate a wide range of walking speeds. Each curve is averaged across 1 minute of walking on a treadmill at each speed.

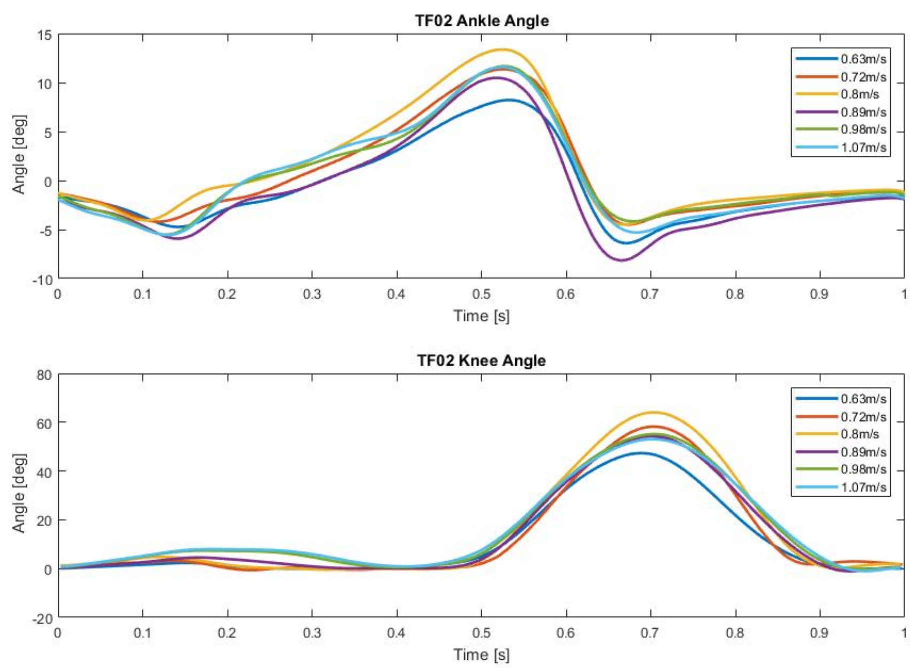


Figure 2: Prosthesis kinematics as a function of walking speed for the second transfemoral amputee subject which demonstrate a similar trend. Similarly, our controller was able to accommodate a wide range of walking speeds for the second subject as well. Each curve is averaged across 1 minute of walking on a treadmill at each speed.

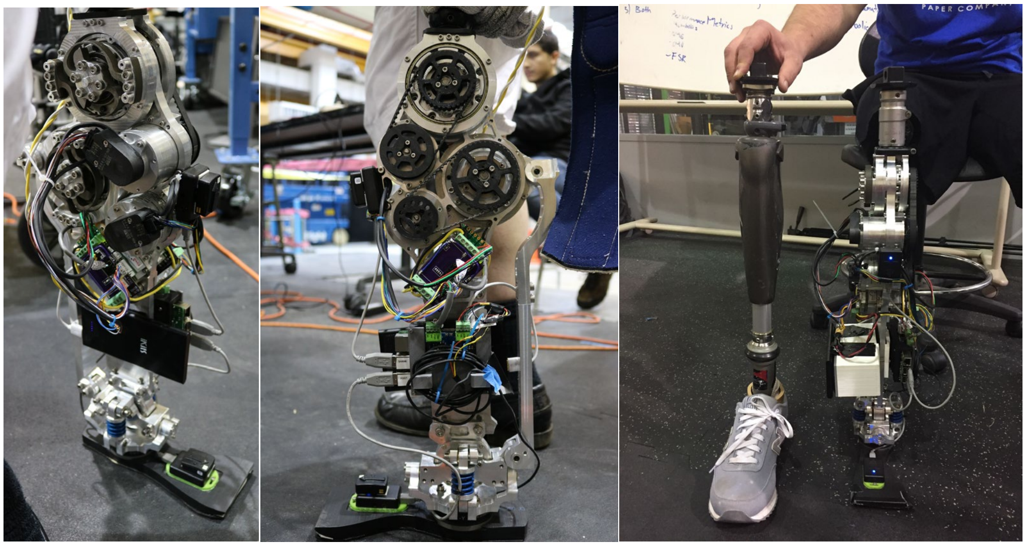


Figure 3: Current state of the device (left two figures). Mechanical improvements throughout the quarter have continued to help increase the robustness of experimental data collections on both able-bodied test subjects and patients with amputation. On the right, we show our alignment procedure in that we change the shank height of the device to align the knee joint center of rotation and ensure the overall build height of the device is the same as the patient's take home device

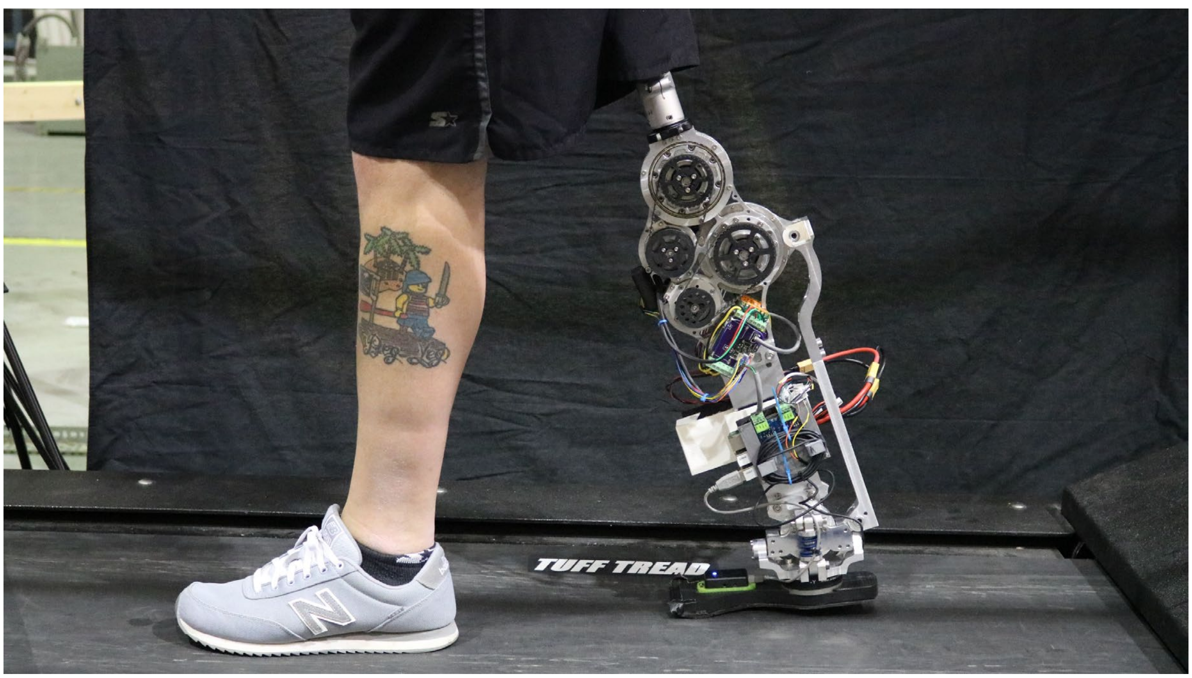


Figure 4: Patient walking on treadmill for walking speed experiment. Each subject was able to walk at a wide range of walking speeds without changing underlying impedance parameters.

Figure 5: Prosthesis testing with an individual with transfemoral amputation on a ramp. Testing has moved to working on controlling the leg and gathering data on ramps on our new terrain park (pictured). The gray tiles show force plate insert locations for collecting biomechanics data.

Quarter 2 Activities and Accomplishments:

Major Task 2: Prepare prosthetic leg for amputee testing

We have been continually working to make improvements to our overall system even though patient testing started around month 9 of the grant. The primary development work that we've been doing over the last three months is to upgrade the electronics package. We need a more robust set of controllers for implementing the machine learning techniques. To this end, we are planning to offload a lot of the low level computations to a separate microcontroller which will free up space on the raspberry pi for running the state machine at a faster rate and running machine learning algorithms.

Major Task 3: Amputee training and initial data collection for pattern recognition systems

This has been a major source of our effort over the last 3 months. In previous months, we had created the functionality of adding the ability to scale equations on impedance parameters easily from the GUI. In April, we began to test these equations in various conditions such as walking speeds and different ambulation modes to allow users to walk in a more natural and smooth manner. In April we finished tuning ramp descent with one pilot transfemoral amputee to ensure that the device was performing well. At the end of April, we were able to have an analysis of kinematic and kinetic data at different conditions under different scaling equations in order to see if adjusting control parameters could lead to a reduction in metabolic cost compared to constant impedance parameters in able bodied subject tests. We have put this set of experiments on hold as we have now turned our focus to amputee subject testing.

In May, the first pilot testing of working with circuits on the terrain park was performed with a single transfemoral amputee. We also recruited two new transfemoral amputees into our study in June who walked on the prosthesis (Figure 6). Kinsey Herrin, our new on the ground prosthetist, successfully fit and aligned both subjects on the device. We then proceeded to tune level walking as well as ramp ascent and descent in the same session with both subjects. Both subjects were easily able to walk on the ramp and over level after their first session.

We also tested with 4 transfemoral amputees in which they were expected to complete a "ramp circuit" multiple times over a range of inclination angles. Powered prosthesis tuning was performed with each subject to allow for the user to feel comfortable walking with the powered device for each ambulation mode (i.e. level walking, ramp ascent, and ramp descent).

The ramp circuit involved starting in standing mode, taking a level walking step, transitioning to ramp ascent, walking up a 16 foot ramp, and transitioning back to level walking, turning around after a few steps on the elevated platform, transitioning to ramp descent, walking down the ramp, and finally transitioning back to level walking (see supporting video for an example of a ramp circuit). For each subject, we collected at 3 different ramp incline angles varying from 8 to 12 degrees. One subject was able to complete a more rigorous “walking speed” protocol which involved walking at approximately 12 different static/constant speeds ranging from 0.6 to 1.2 m/s on a force instrumented treadmill and 3 dynamic trials where walking speed was changing throughout the trial (see supporting video for a ‘fast’ walking trial on the treadmill). This was the next step in progressing to achieve a real-time machine learning algorithm that could estimate walking speed by giving us robust training data to test our model to a greater extent than what was collected earlier in the year for the Dynamic Walking presentation. Overall in the last quarter, we were able to collect more data with able-bodied subjects and amputees (~10 more able-bodied sessions and ~ 10 more sessions with various transfemoral amputees).

Major Task 4: System Implementation

In May, we presented at a Dynamic Walking conference, where we presented a continuous walking speed estimation using a regression machine learning algorithm with data collected on our prosthetic device. Two transfemoral subjects were asked to walk at a range of walking speeds from 0.63 m/s to 1.07 m/s. We used embedded mechanical sensors on the prosthesis (i.e. encoders, load cell, and IMU’s) as input feature signals in order to generate a good model that could estimate walking speed. We have begun analyzing both the walking speed and ramp data to begin creating robust machine learning algorithms to estimate walking speed and ramp transitions/inclination angle in a user-independent manner. Initial results (user-dependent) are shown in Figure 7 for walking speed estimation.

In June, two papers were accepted to the ASME DSCC conference later this fall (See Appendices B and C). One paper discussed how a simulation model of the prosthetic device could be used to better inform the person tuning the device to select different impedance parameters depending on the target kinematic trajectory. The simulation was performed using ROS and an accompanying software package called Gazebo. The results showed that we could achieve a mean absolute error of approximately 10%. The simulation framework is displayed in Figure 8. The other paper described how the mechanical device of the leg as well as the control architecture was designed/structured. We showed that the powered prosthetic device was able to match able-bodied kinematics and kinetics found in previous literature (Figure 9). We plan to include both these full papers as supporting material in the year-end report.

Major Task 6: Comparison of clinical parameters of powered prosthesis compared to passive prosthesis

We have begun to prepare for a comparison of powered vs passive prostheses for our Specific Aim #3. Primarily, this has involved setting up equipment for biomechanical measurements. We were able to sync our motion capture system with both our EMG systems and initial pilot testing was performed of looking at EMG information in respect with the motion capture system with an able-bodied subject wearing the prosthetic device via an iWalk adapter. We have practiced putting on motion capture on both the sound side and the prosthesis device and plan to test with a pilot amputee subject in July.

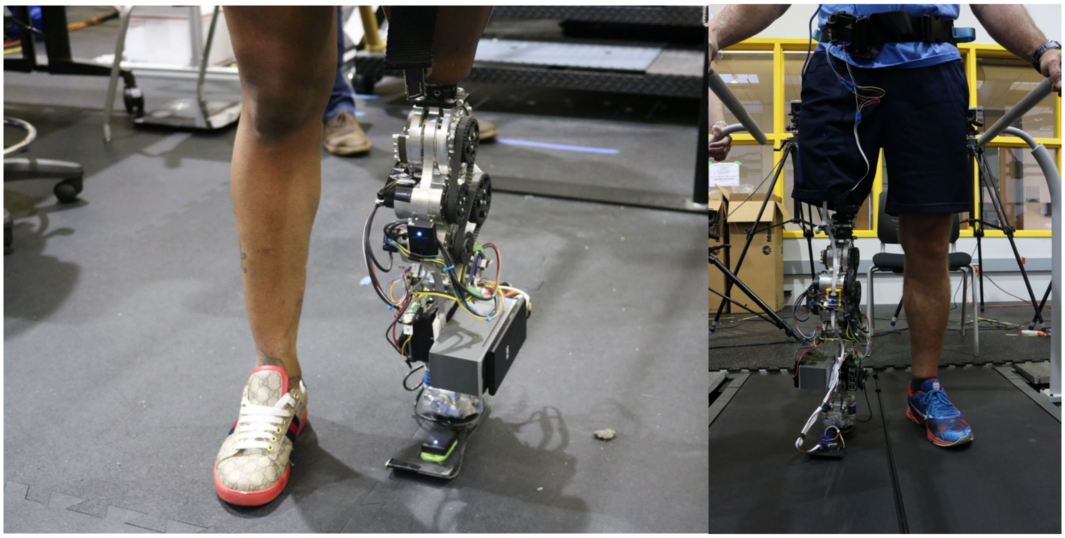


Figure 6: Left - One of our new transfemoral participants walking on the powered leg in the parallel bars. Right – Experienced patient using the leg for a variable walking speed trial on our new Bertec (force instrumented) treadmill.

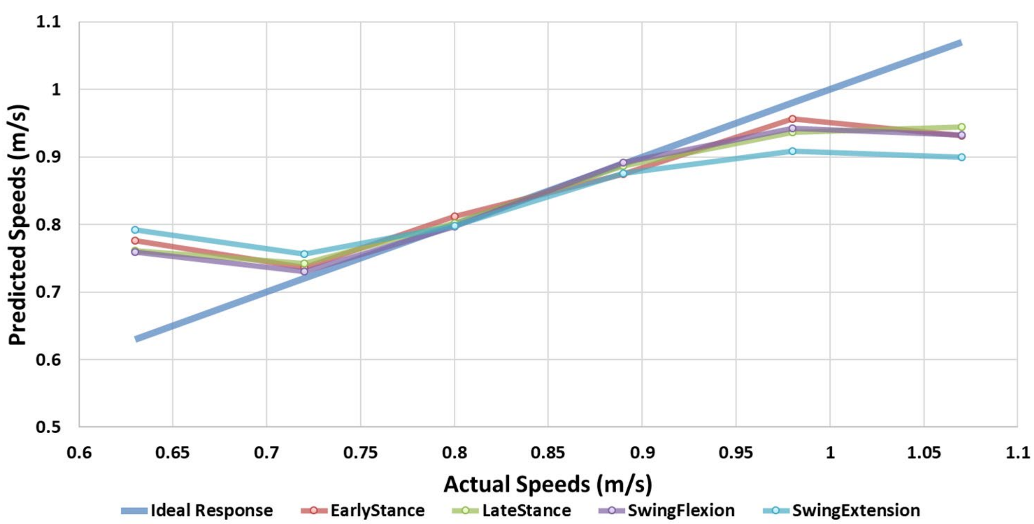


Figure 7: Machine learning capability for estimating walking speed. In this analysis, the data at the predicted speed was withheld from the machine learner and it has to predict the withheld data by regressing across the other walking speeds. We found that the machine learning techniques did an excellent job with interpolating walking speed between points in the training set, but did not extrapolate well at the edges. This supports that the machine learning strategy is feasible, but training data at the highest and lowest walking speeds is need in order to get robust results. Overall, we were able to predict walking speed with an average error of 0.1 m/s which we believe is accurate enough for excellent real-time scaling of device parameters with walking speed.

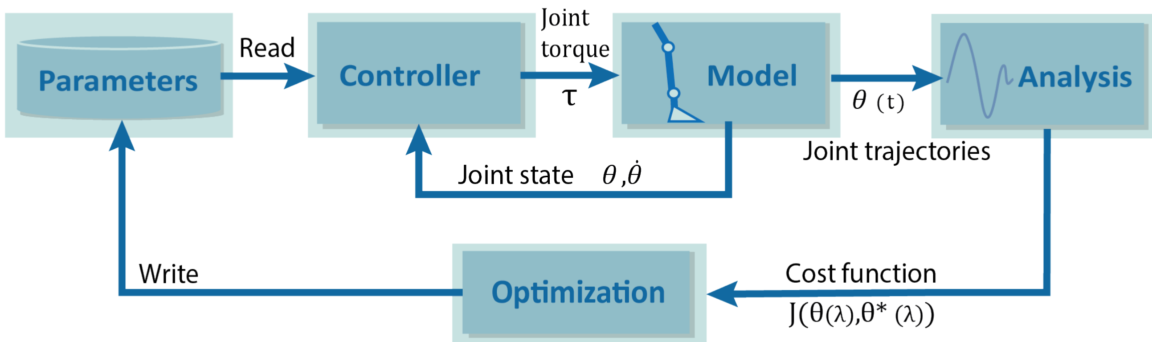


Figure 8: Overview of the optimization process: the controller module executes the power prosthesis controller firmware based on ROS. Model is the virtual representation of the device in the Gazebo environment. Simulation results are analyzed using a biological trajectory reference, creating an optimization cost function that is used in a pattern search optimization that sets the parameters for the device operation.

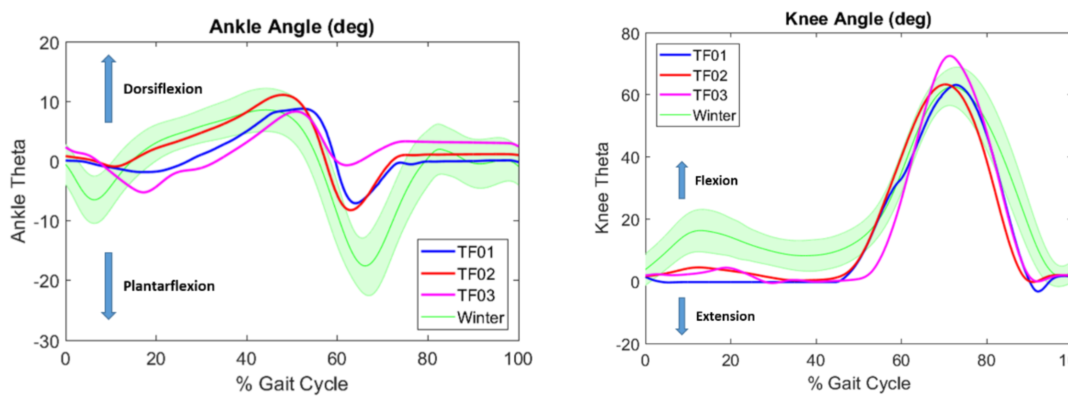


Figure 9: Kinematic data from ankle (left) and knee (right) joints on a prosthetic device, averaged and segmented over 40 strides plotted versus percent gait cycle compared to healthy biomechanics [Winter, 1990]. We believe our device is doing an excellent job of replicating biological human kinematics which is a desirable characteristic for a prosthetic leg.

Quarter 3 Activities and Accomplishments:

Major Task 2: Prepare prosthetic leg for amputee testing

We have been continually working to make improvements to our overall system even though patient testing started around month 9 of the grant. The primary development work that we've been doing over the last three months is to upgrade the electronics package. While the construction was on-going, we used this downtime to finalize a new electronics system that will be implemented in new experimental protocols. This new electronics system utilizes a micro-controller that is responsible for handling all of the low level control of reading encoder positions of both motors and loadcell and sending up relevant information to the mid-level controller. The mid-level controller is responsible for changing between states in a finite state machine that discretizes the gait cycle. The low-level control also calculates the desired torque and transforms this into a current that is sent to the motor drivers to actuate each joint. With this new system, it will be easy to also add closed-loop torque control to the device. We also developed the mechanical structure to be mounted that enables SEA to be implemented onto the device. Overall the new electronics system is faster and will add better robustness to continue for longer periods of time.

Major Task 3: Amputee training and initial data collection for pattern recognition systems

In July, we focused heavily on testing with various transfemoral amputees (~10 more sessions). When testing with transfemoral amputees they were expected to complete a "ramp circuit" multiple times over a range of inclination angles (Figure 11). Preliminary tuning was performed with each subject to allow for the user to feel comfortable walking with the powered device compared to their passive devices for each ambulation mode (i.e. level walking, ramp ascent, and ramp descent).

The ramp circuit involved starting in standing mode, taking a level walking step, transitioning to ramp ascent, transitioning back to level walking, transitioning to ramp descent, and finally transitioning back to level walking. Sensors included in this circuit involved inertial measurement units, encoders, and six-axis load cell embedded onto the prosthetic device. Six different ramp inclination angles were tested with at least 3 trials at each incline (trials after all tuning and accommodation was complete).

Since the previous report, we were able to collect another subject that was able to complete a more rigorous "walking speed" protocol which involved walking at approximately 12 different static/constant speeds on a force instrumented treadmill and 3 dynamic trials. This data has been used heavily for preparing for System Implementation (see below).

In the end of September, we recruited another transfemoral amputee to bring us to a total of 7 people (Figure 10). We performed an initial tuning and fitting with the new person and begin initial tuning. We will resume our normal operation of collecting data this quarter.

Major Task 4: System Implementation

We have begun developing a structure of training this data off-line and creating machine learning algorithms that can eventually be implemented on our device in real-time. Hence 3 main areas that are being explored include intent recognition, slope estimation, and walking speed estimation. For intent recognition, we have begun working on classification models to characterize the transitions to/from the ramp with our initial data collected with patients.

One of the analyses we have done is to look at the contributions of each sensor on the prosthesis for intent recognition. Combinations of 6 axis load cell, IMU (foot vs shank vs thigh), and joint encoders were analyzed (Figure 12). To evaluate the sensitivity of the features, the selected windows were further characterized as either transition or steady state, where transition steps transitioned to a different mode, while steady state steps stay in the same mode. From these characterizations, two types of error can be analyzed:

$$transitional\ error = \frac{\#\ misclassified\ transition\ steps}{total\ \#\ of\ transition\ steps}$$

$$steady\ state\ error = \frac{\#\ misclassified\ steady\ state\ steps}{total\ \#\ of\ steady\ state\ steps}$$

Figure 12 and 13 shows forward sensor selection being applied using a linear discriminant analysis (LDA) as a classifier. Individually, the foot sensor was most useful for minimizing error, with the steady state error achieved being 5.8 % and transition error being 16.1%. This may be due to the acceleration profiles (X, Y, and Z direction) recorded by the foot IMU being more differentiable between modes compared to other sensors. Knee joint encoder provides the least value of all sensors for both steady state and transition errors. For LDA, although similar sensor minimizing steady state errors (7.35%). Based on our initial assessments, it appears that including IMUs on the foot, shank and thigh each have value added for improving intent recognition capability.

Major Task 6: Comparison of clinical parameters of powered prosthesis compared to passive prosthesis

We have begun to prepare for a comparison of powered vs passive prostheses for our Specific Aim #3. In the end of July, we also performed a pilot experiment with 1 transfemoral amputee to begin doing a passive versus active comparison of prosthetic devices using motion capture analysis on a force-instrumented treadmill. We submitted an abstract to the American Academy of Orthotists & Prosthetists - 45th Academy Annual Meeting & Scientific Symposium and are currently under review based on this pilot work (see Appendix E). This experiment allowed us to begin thinking about how we can use motion capture on the device to compare sound and affected limb kinematics and kinetics.

In the months of August and September, the lab was “shutdown” due to construction to add equipment to increase functionality of the lab. See Figure 14 for a picture showing off the new gait lab and some of the associated functionality. First, the motion capture system was suspended around our “experimental area” which allows us to capture motion capture on the terrain park, force-instrumented treadmill, and overground area with embedded force plates. We have also added a safety harness system that can go around the entire lab to ensure user safety. We have also received and been trained on a new metabolic system (K5-COSMED) which allows for breath by breath energy expenditure analysis. New force plate mounts were added throughout the lab for overground dynamics assessment. A patient changing room was built to help with subject prep.

Figure 10: Left - One of our new transfemoral participants walking on the powered leg in the new harness system over force plates. This patient is a low K3 ambulator and had extremely high enthusiasm for walking with the powered leg in his written clinical outcome measures (PEQ – validated clinical outcome measure, see Appendix F).

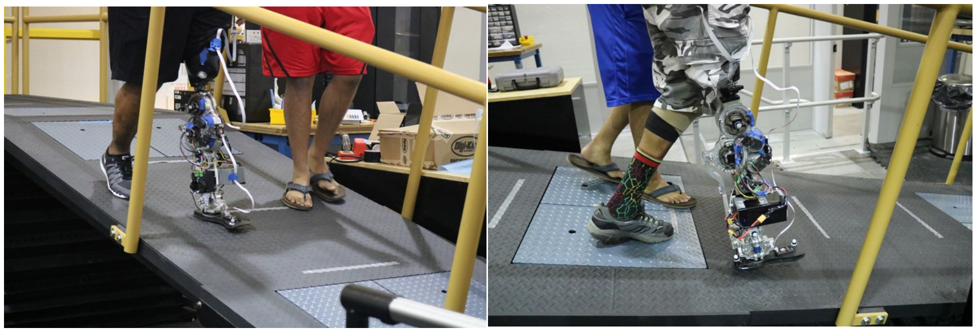


Figure 11: Demonstration of ramp walking. We now have successfully trained four transfemoral amputees to use the powered prosthesis to ascend/descent the ramp. Additionally, three of those have now completed the ramp experimental protocol which involves walking up and down the ramp 3 times at each of 6 different ramp incline angles (from 5 to 14 degrees).

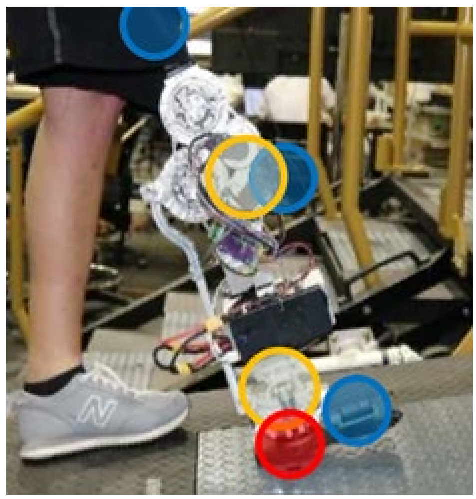
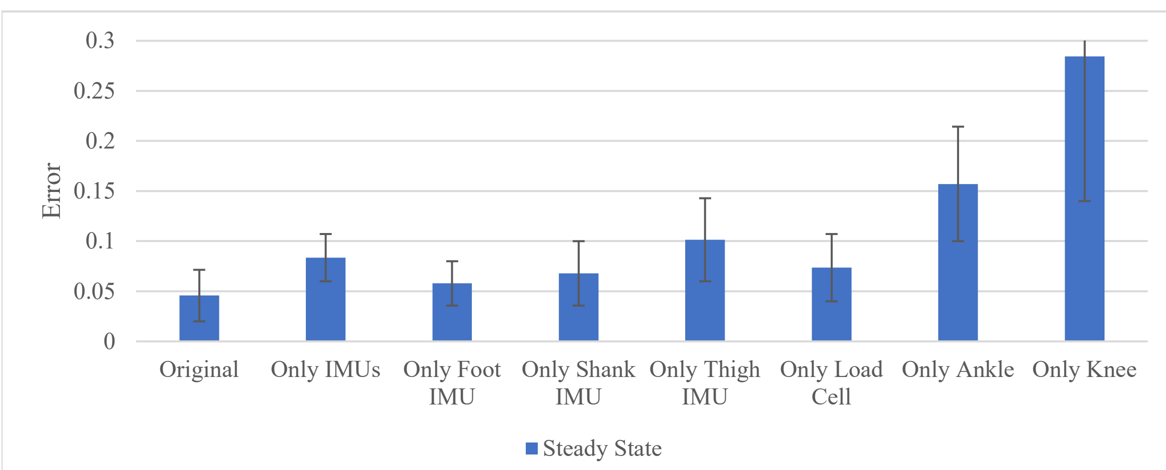


Figure 12: Sensor placement on the powered prosthesis, IMUs (blue) on foot, shank, and thigh. 6-DOF load cell (red) on foot. Knee and ankle joint encoders (orange).



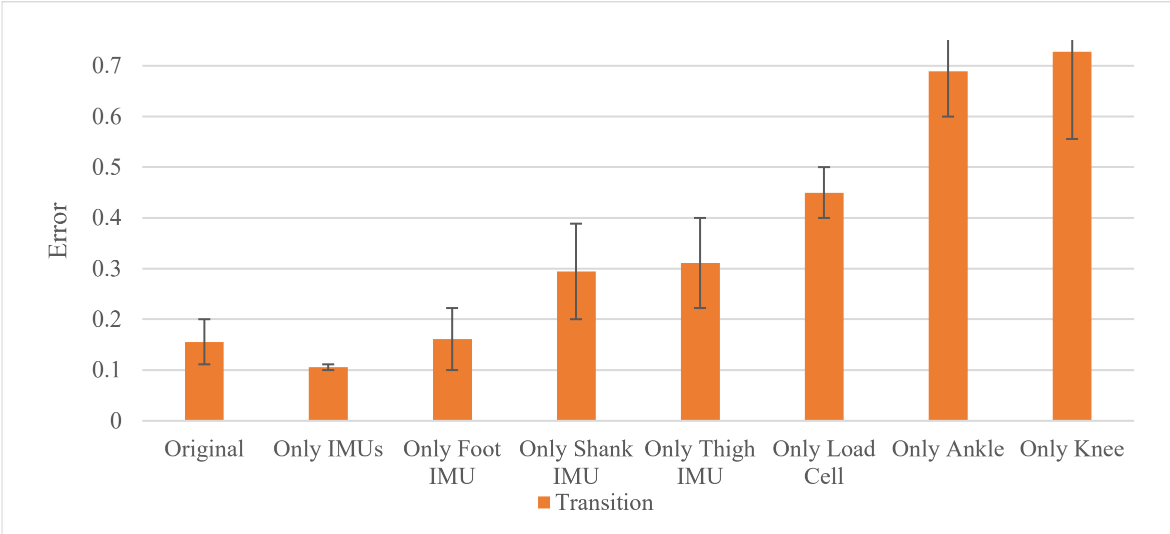


Figure 13: Forward sensor selection being applied using a linear discriminant analysis (LDA) as a classifier. Individually, the foot sensor was most useful for minimizing error, with the steady state error achieved being 5.8 % and transition error being 16.1%. This may be due to the acceleration profiles (X, Y, and Z direction) recorded by the foot IMU being more differentiable between modes compared to other sensors. Knee joint encoder provides the least value of all sensors for both steady state (top) and transition (bottom) errors. For LDA, although similar sensor trends are observed in minimizing steady state and transition errors, the load cell is more useful for minimizing steady state errors (7.35%).

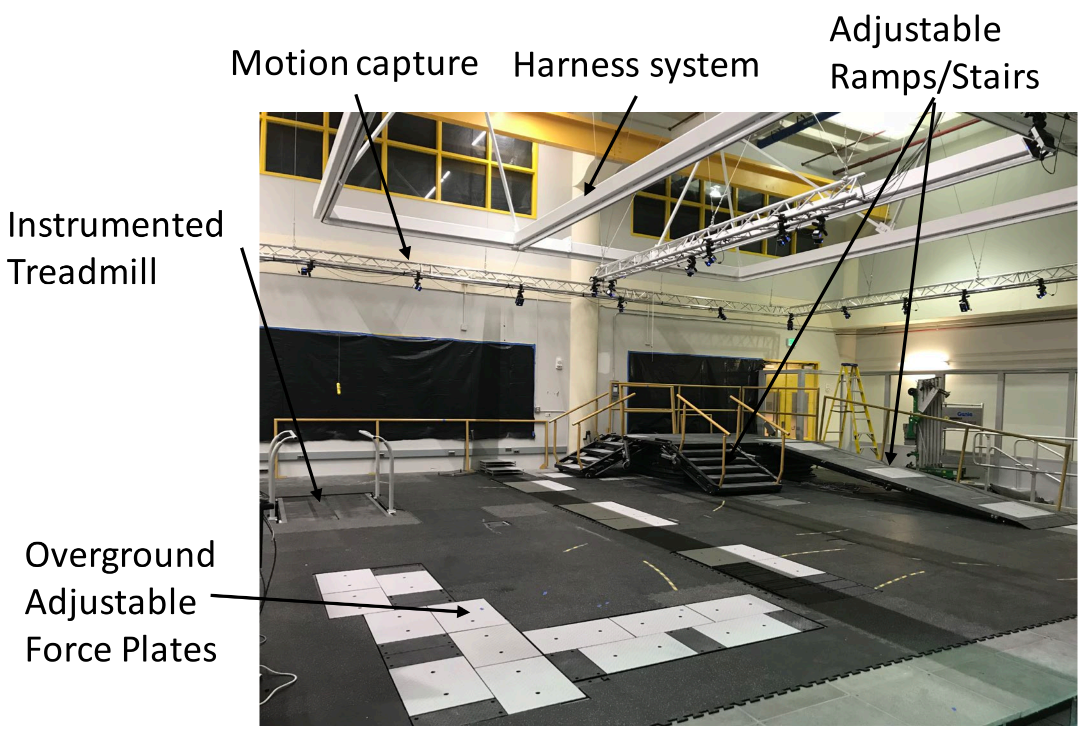


Figure 14: New gait lab that has been renovated over the summer. We now have a completed terrain park with force plate inserts in the ramp and stairs and force plates in front of the stairs and ramps to capture transitions. Additionally, we have force plates in the level walkway to capture steps on the level and going around turns. Our force treadmill (Bertec) is level with the ground. A full harness system has been installed over head with multiple trollies with harnesses for fall arrest, body weight support, pediatric, and bariatric populations. A Vicon, 34 camera system surrounds the entire area allowing full capture inside the volume of the lab. The terrain park is adjustable to accommodate a wide variety of stair heights and ramp inclination angles. We have substantially increased the size and capability of the lab with the renovations over the summer and we believe this will significantly help the grant activities.

Quarter 4 Activities and Accomplishments:

Major Task 2: Prepare prosthetic leg for amputee testing

We have been continually working to make improvements to our overall system even though patient testing started around month 9 of the grant. The primary development work that was done in October/mid-November was to finalize and validate that the electronics package was able to handle all of the new functionality to allow for smoother and more robust control. This new electronics system utilizes a micro-controller that is responsible for handling all of the low level control of reading encoder positions of both motors and loadcell and sending up relevant information to the mid-level controller. The torsional springs stiffness values were validated using a test rig in an axial loading machine to ensure that computer simulated modeling stiffness values matched actual stiffness values. Another aspect that was improved upon was the wiring between various sensors and the raspberry pi using newly manufactured printed circuit boards to ensure all the electronics would be on-board the device. This allowed for more stable and robust wire management between all of the electronics, as seen in Figure 15.

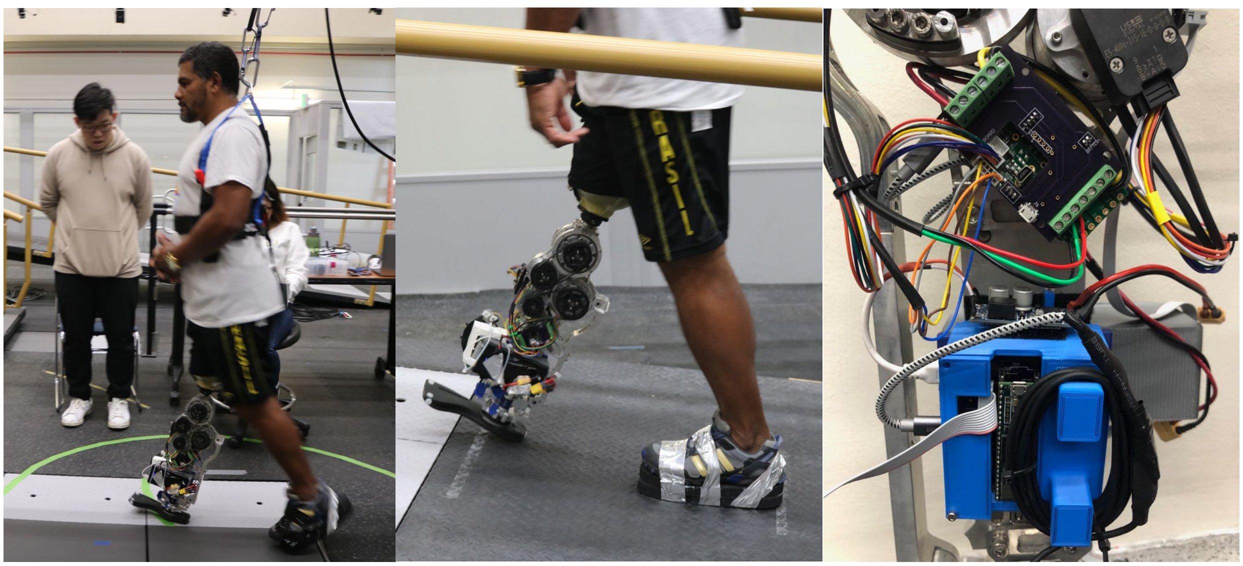


Figure 15: One of our new transfemoral participants walking on the powered leg in the new harness system over force plates (left) and ramps (middle). This patient is a K4 ambulator and had extremely high enthusiasm for walking with the powered prosthesis. The new electronics package in a compact blue case (right).

Major Task 3: Amputee training and initial data collection for pattern recognition systems

After the construction was completed in October, we resumed our normal operation of data collection. In order to create a suitable walking speed estimator, we focused on a getting an adequate number of transfemoral amputee to complete a more rigorous “walking speed” protocol which involved walking at different static walking speeds on a force-instrumented treadmill ranging from 0.5 m/s to their maximum preferred speed. We also are recording motion capture data for all of trials in order to better understand the underlying biomechanics seen in amputees (i.e. sound vs. prosthesis). We also instrumented each subject with a set of markers on their sound limb and torso as well as their respective prosthesis (see Major task 6). Preliminary tuning was performed with each subject to allow for the user to feel comfortable walking with the powered device compared to their passive devices for each ambulation mode (i.e. level walking, ramp ascent, and ramp descent) before walking on the treadmill.

Since the previous report, we were able to collect a total of 6 subjects through this protocol, with a planned 7th in the next quarter. This data will be used in helping prepare for System Implementation (see below). In the last quarter, we recruited and trained two additional patients with transfemoral amputation which brings our recruitment numbers to a total of 9 which was the original number proposed for this grant. We performed an initial tuning and fitting with the new people and begin initial tuning. One of the subjects that was fit a year ago also came in and was trained to use the device for the first time during this quarter. We will finish the last person in the walking speed protocol, and move towards collecting a comprehensive data set of stairs and ramps that include encoder, inertial measurement units, six-axis loadcell and biomechanics information to be used in developing smart intent recognition algorithms.

We were invited to submit a follow up journal paper to our MHSRS conference submission to the MHSRS 2018 Supplements (See Appendix A). A journal paper was submitted to MHSRS Supplement to Military Medicine Update in November 2018. This paper showed how impedance parameters were tuned across users and ambulation modes to show the ease of using our implemented mid-level controller consisting of an impedance controller paired with a finite state machine. We show some of our initial kinematic results with patients using the device. This paper is under review at the moment and will be provided as a supplement in a future report once it is in final form and accepted for publication.

Major Task 4: System Implementation

The data collection infrastructure developed on the prosthesis forms an excellent basis for real-time slope prediction. These data can be learned from using machine learning algorithms (i.e. neural networks) to determine the ground slope a user is currently experiencing. We can use this prediction to alter certain parameters of the device to give more appropriate assistance and improve their biomechanics while walking on slopes. In the process of investigating the results of different policies, it is important to separate the data into two groups: steady state examples (steps in which there is no change in ambulation mode) and transition examples (steps during which occurs a step from one ambulation mode of level-walking, ramp ascent or ramp descent to another). Transition steps require more time to determine the ground slope and are generally harder to produce reliable estimates. One initial option is to train a machine learning system with only transition data which is displayed in Figure 16.

As can be seen, this strategy reduces the error and also the standard deviation of the mean of the transitional examples; however, it drastically increases the error associated with the steady state examples. With this large amount of mean absolute error (MAE), the output is unusable. An immediate tradeoff is evident between transitional and steady state error using this strategy. This could be remedied by crafting two neural network models, one for transition examples, during a transitional step, and one for steady state examples during all other times. This could capitalize on the lower error during transitions, but allow the steady state error to remain low. The next idea to reduce the transitional error stems from the fact that for a given subject, there are very few transitional examples. One method to increase the number of data points for an algorithm to learn from involves using data previously acquired from other subjects. Concatenating the data from four subjects resulted in surprising results, as seen in Figure 17.

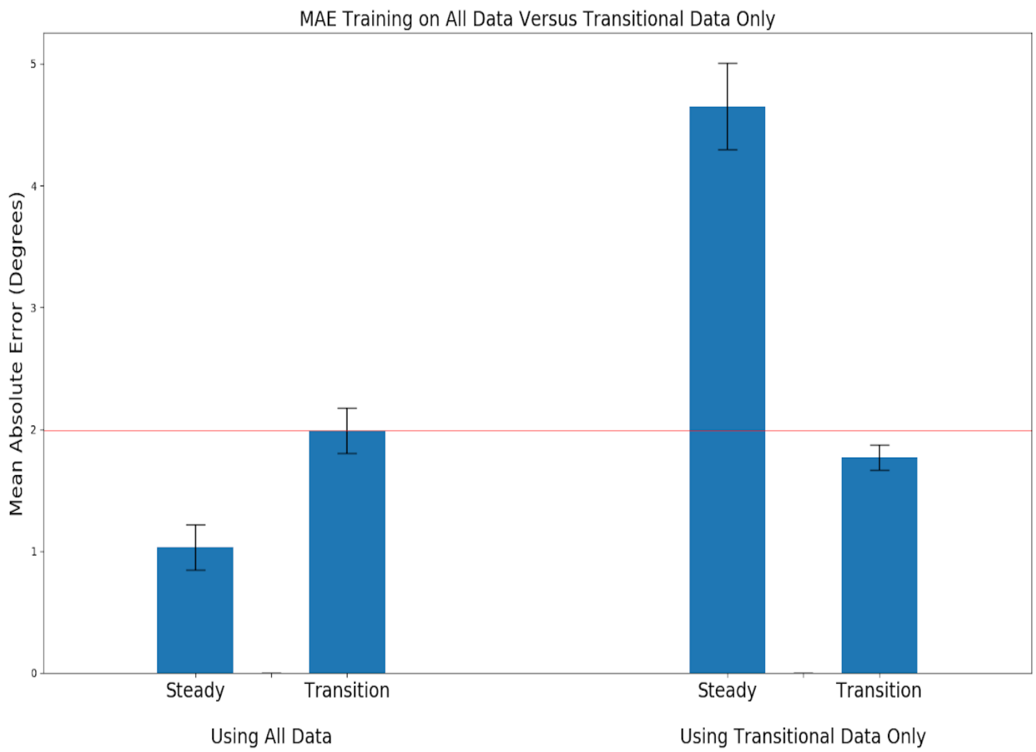


Figure 16: Estimating slope inclination angles by training on all data versus only transitional data using a neural network algorithm.

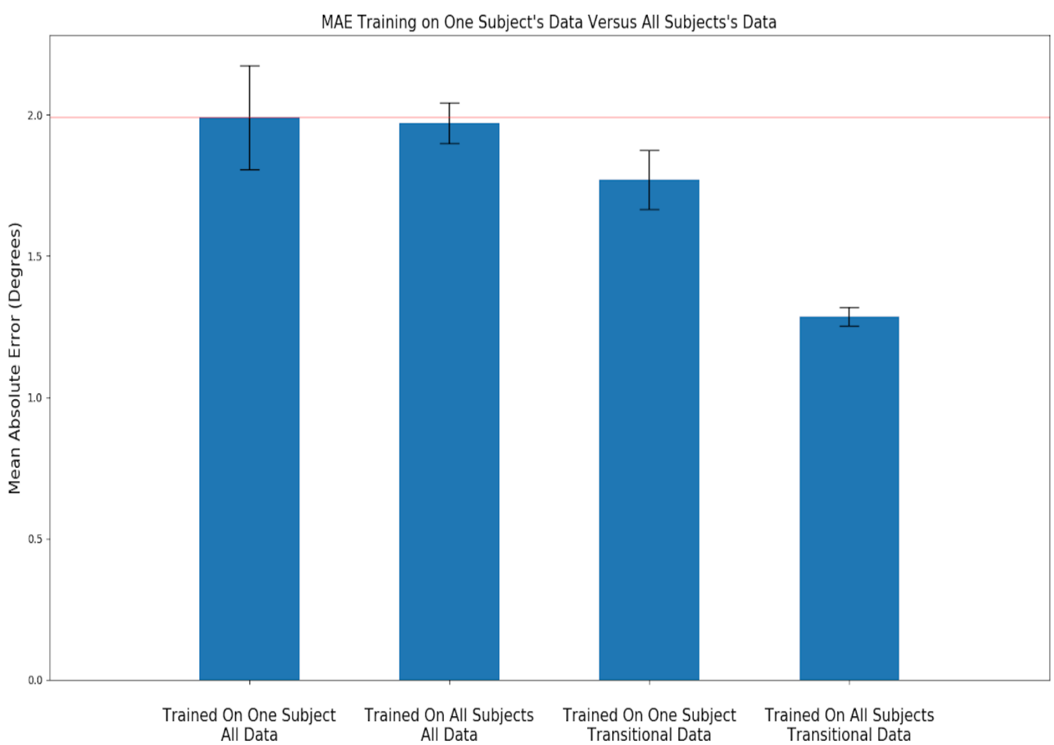


Figure 17: Reduction in mean absolute error can be achieved by concatenating prior subjects to give the machine learning algorithm more to learn from.

The key results to notice is how training on transitional data once again lowered error across the board. The new strategy of using all available data did not help much when the steady state examples were left in the datasets. However, combining the two methods separating models for steady state and transition steps and training on one large dataset from all the subjects resulted in a much lower error and smaller deviation across subjects. A final strategy that we have considered is to separate the data into separate models for ramp ascent vs ramp descent due to the varying sensor patterns between the two tasks. The results of separating the data into these two groups is shown in Figure 18, while also showing the effect of the previous policy. Again, augmenting the transitional data with other subjects' data yields decent reductions on the error and deviation. The red line in this plot shows the minimum error from the previous figure. In all cases, separating the data into ascent and descent data yields a lower error, finally below one degree of mean absolute error. If a classifier separated the examples into ramp ascent or ramp descent examples, the regression models would be able to generate much better predictions. The final error of this system (less than 1 degree of slope mean error) is very promising as a system for implementation on the prosthesis. We are now working to get our slope estimation system implemented in real time as well as a classifier for recognizing mode changes, which will aid with slope determination at the transition steps.

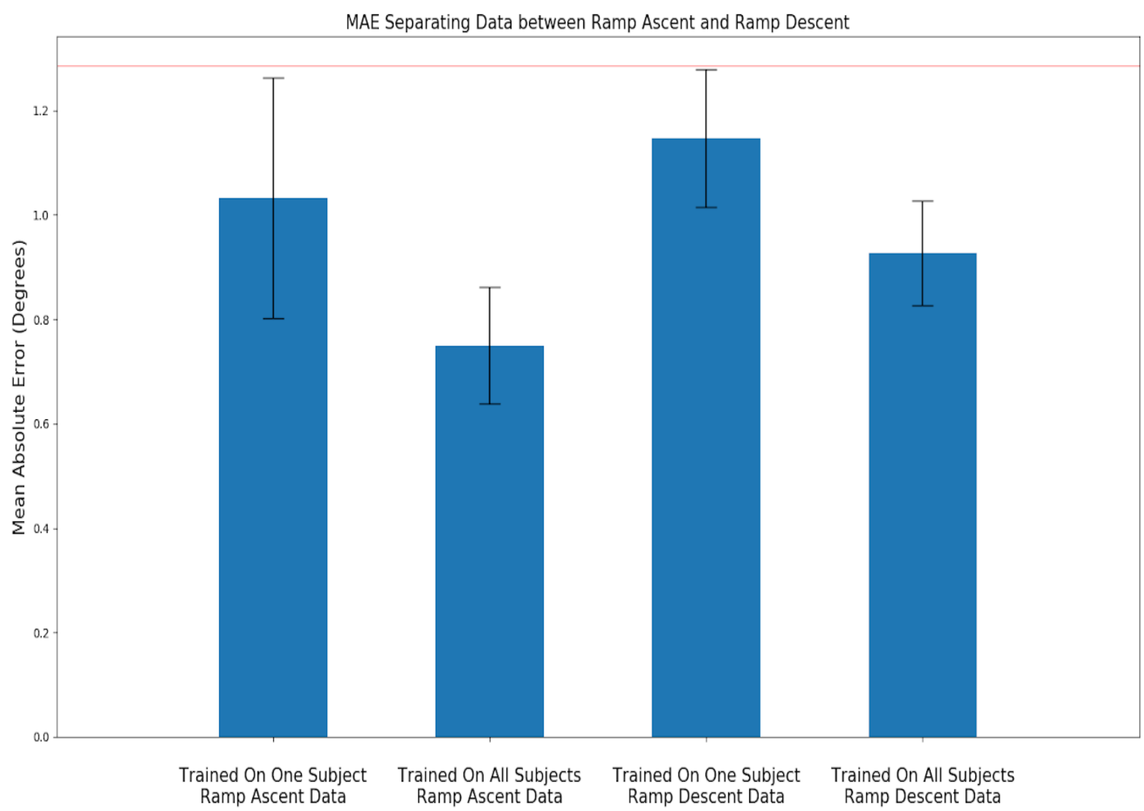


Figure 18: Reduction in mean absolute error by only training on separate ambulation mode transitions by comparing between a single subject and all available subjects.

Major Task 6: Comparison of clinical parameters of powered prosthesis compared to passive prosthesis

We have begun to prepare for a comparison of powered vs passive prostheses for our Specific Aim #3. In the end of July, we also performed a pilot experiment with 1 transfemoral amputee to begin doing a passive versus active comparison of prosthetic devices using motion capture analysis on a force-instrumented treadmill. Our abstract to the American Academy of Orthotists & Prosthetists - 44th Academy Annual Meeting & Scientific Symposium was accepted on the pilot work from the summer. During Q4, we performed an experiment to directly compare passive prosthesis ambulation with powered prosthesis ambulation using our experimental device with N=6 individuals with transfemoral amputation. We did this comparison at level walking on the treadmill, slope ascent on the treadmill, and slope descent on the treadmill. We formally collected bilateral biomechanical data (including motion capture and force plates) to compare kinematics and kinetics of walking with the powered prosthesis compared to their take home passive device, as seen in Figure 19. Our primary hypothesis is that the prosthesis will better replicate human biomechanics (kinematics and kinetics) compared to a passive device. We also will analyze if supplying more human like biomechanics on the device will alter intact joint biomechanics. The desired outcome is to eventually reduce the excess joint loads on the four biological joints (non-amputated side hip, knee and ankle, and amputated side hip). We believe this initial assessment will help inform how we can change the controller to provide better assistance to individuals with a transfemoral amputation using powered prostheses.

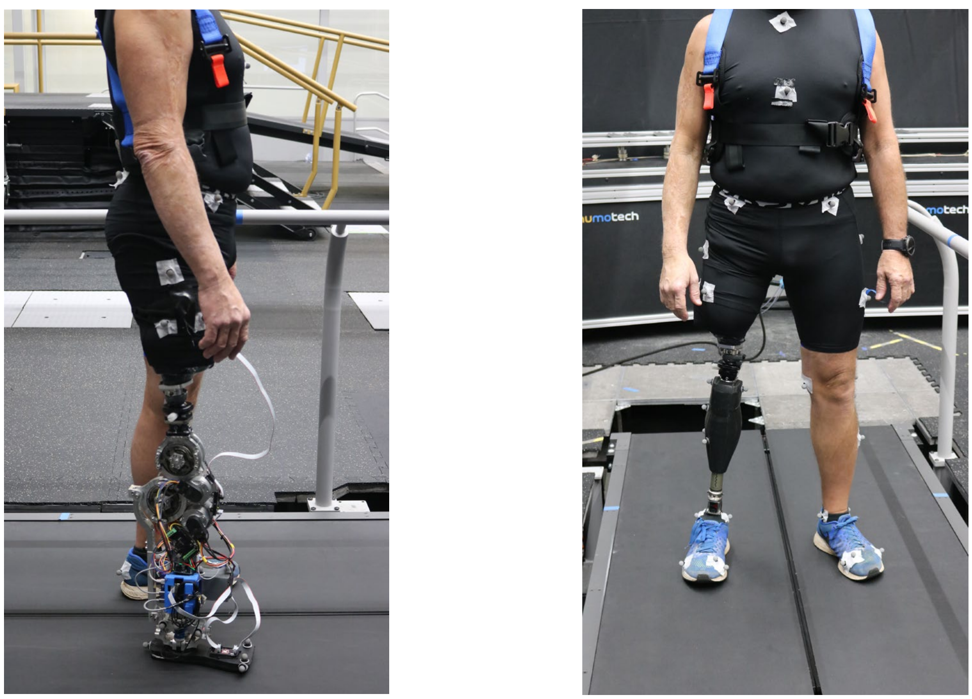


Figure 19: Motion capture on both the powered prosthesis (left) vs. passive device (right). Data was captured on a force-instrumented treadmill in a level ground, incline, and decline configurations.

In order to begin how to compare biomechanics of the sound limb versus prostheses, we developed several models in OpenSim, an open-source software that allows for modeling, simulating, and analyzing the neuromusculoskeletal system. Since this software typically deals with able-bodied individuals, we had to configure our models to include the powered prosthesis in the both the left and right configurations in order to begin performing inverse kinematics and inverse dynamics. The models also needed to be validated which can be seen in Figure 20. We will continue to analyze biomechanics data and report on these in more detail in a future report.

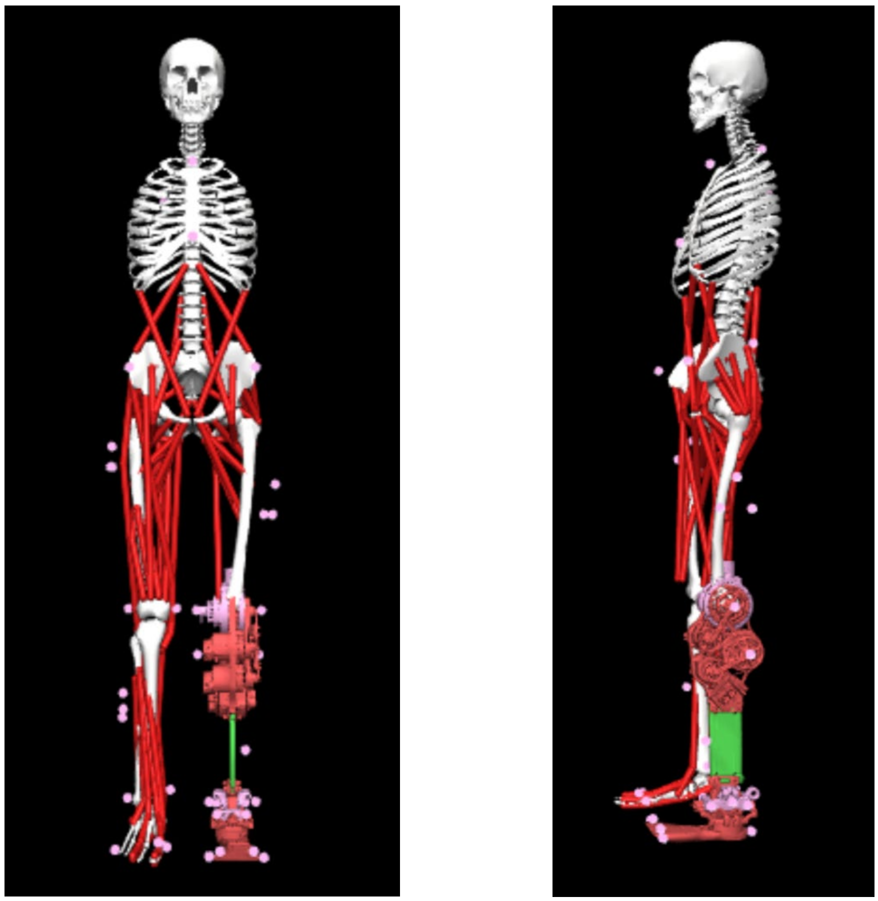


Figure 20: OpenSim models created in order to better perform biomechanical analysis of calculating kinematics and kinetics using forceplates and motion capture.

Q4 Results and Discussion:

We have now been able to successfully train nine individuals with transfemoral amputation to walk on the device in different walking modes (i.e. overground and ramps). One major achievement this quarter has been able to update the stability of our controllers to allow for smoother walking steps and transitions. We submitted a journal paper demonstrating the ease of using an impedance controller paired with a finite state machine. The control system was able to correctly and robustly identify the phase of gait, set gait phase specific impedance, and generate near normal lower limb kinematics using minimal tuning of impedance parameters (7 out of 84). This controller was also capable of scaling powered assistance to the user across a range of walking speeds and inclination grades, which restored functionality lost through amputation.

Next, we have been able to make significant progress in developing implementable machine learning algorithms that can be used in real-time in the future. We have shown that we are able to create relatively accurate machine learned models that can predict walking speed and slope inclination angles in our offline analyses (seen in figures above). We will continue to expand our framework in the next couple of quarters to ensure we can use these models in real-time and update device parameters to easily adapt to the environment.

In Quarter 4 we had started integrating motion capture and force plates into our data collection protocols to allow us to analyze biomechanical data in a variety of contexts. We have developed several OpenSim models to help us perform a more thorough biomechanical analysis (i.e. inverse dynamics and kinematics) to compare between the sound and affected side when walking. We have basic pipelines developed for calculating the inverse dynamics and plan to expand on this analysis over the next couple of quarters including extending to ramp and stair ambulation.

What opportunities for training and professional development has the project provided?

Training and Professional Development:
This project provided significant training for a large range of individuals (see project personnel). This included training for 3 primary groups: 1) Graduate students in Mechanical Engineering and Robotics, 2) Professional Graduate students in the Prosthetics and Orthotics program at Georgia Tech (2 students), 3) Physical Therapist Graduate students in Emory's PT program (4 students) and 4) Undergraduate training for students in Mechanical, electrical, computer, and biomedical engineering as well as computer science. Training programs included a weekly overall project meeting that rotated between 3 topics: 1) Training session led by PI Young on a technical topic, 2) Journal club on related research, 3) Student presentations on work to date and future plans. These meetings helped to train the study team, share results, and learn about updates in the field. Additionally, PI Young met with the project leaders (graduate students) on a weekly basis. These meetings were specifically for project planning and also aiding the graduate students in learning how to perform the studies for the grant. Additional day-to-day training was provided as needed by the PI for the study team. A joint biweekly meeting with the Sawicki lab has occurred throughout the year, which included significant training in research methodology and has been a valuable added training tool for the team. Also, PI Young continued a Vertically Integrated Project (VIP) at Georgia Tech to increase undergraduate participation and training in research. This project was featured as one of the primary sub-teams in the overall VIP team called "Robotic Human Augmentation". Essentially, this program provides structured training both through the program and the PI as a team of undergrads works on a specific project. A team of 6-8 undergraduates worked on this project each semester through this program, which provides communication and scientific skills. This program also helps to provide professional development as the undergrads in the VIP program present at two research seminar session each semester. The graduate students also had a number of professional development opportunities through presentations of their work to date on the project at internal poster sessions and workshops at Georgia Tech for graduate students. Lastly, PI Young hosted a workshop in May 2018 in conjunction with Freedom Innovations to display their microprocessor knee and how they performed clinical fittings to aid the Georgia Tech P&O crowd on best practices for clinical fitting and calibration of advanced knee/ankle prostheses.

How were the results disseminated to communities of interest?

We provided significant outreach to K-12 students throughout the year, but especially during Robotic Week in April at Georgia Tech. A large number of school groups toured PI Young's lab and a demo of the prosthetic device was available and really helped increase interest in the field. The powered leg platform is visually attractive and was of great interest to a large number of younger participants. We also provided a number of lab tours upon request of local schools and communities. This project really helped to stimulate interest in the field by showing a real application to directly impact clinical care.

Describe briefly what you plan to do during the next reporting period to accomplish the goals and objectives.

1. We plan to continue patient experiments to advance our training and data collection protocols for the grant activities. We will finish our "walking speed protocol" to give us N=7 as well as start a new protocol of collecting stairs, ramps, and overground trials. In this new protocol, we will collect information from our sensor suite to be used in our system implementation as well as collecting biomechanics with our motion capture system

2. We plan to finish modeling and validating both active and passive prostheses in OpenSim to begin performing more in depth biomechanics analysis. We will develop pipelines to process data through Vicon (i.e. motion capture system) to be passed onto OpenSim, where inverse kinematics and inverse dynamics will be calculated. Since no prior models have been created, we will have to confirm whether our modeled/simulated outputs match actual device dynamics by comparing kinematics and kinetics from both sides.
3. We have continued to make modifications to improve the leg and its functionality. We will construct a casing for the device for improved and sustainable functionality as well as a preventative measure to ensure no wires are damaged. We will also want to benchtop test the new closed loop torque control with the new SEA configuration before implementing on the device.
4. We will begin performing trials of real-time machine learning algorithms. We will begin with trying to ensure that a reasonable output can be generated from the machine learning predictor specifically for slope estimation. If successful, we will look to improve our scaling equations to add greater flexibility in control by adapting to the real-time output of inclination angle.
5. We will look into building a new active prosthesis (i.e. Open Source leg from University of Michigan). We will look into purchasing new hardware and electronics in creating a lighter powered prosthesis as our next platform. We plan to use our existing code framework and incorporate our developed controllers and machine learning algorithms on the new device.

4. **IMPACT:** Describe distinctive contributions, major accomplishments, innovations, successes, or any change in practice or behavior that has come about as a result of the project relative to:

What was the impact on the development of the principal discipline(s) of the project?

Our project is likely to make an impact in the field by advancing the state-of-the-art in control of powered prosthetic legs for improving clinical outcomes with patients with transfemoral amputation. In particular, we expect smarter algorithms to predict what a patient is trying to do and provide the correct set of directions to a robotic assistive prosthesis to provide adequate support. For example, if a patient is trying to ascend a set of stairs, we are designing a system that anticipates this desire and provides automatic and natural support through a powered prosthesis to help a patient walk, ascend a set of stairs and continue to walk. A key advantage of this technology is being able to provide active power generation at the knee and ankle, which allows us to help a patient similar to what biological muscles do. We hope to fully restore assistive capabilities on the amputated side such that both lower limbs are providing similar amount of overall work. This would help solve a huge issue in the field in that patients with amputation tend to rely on their non-amputated side much more than their prosthesis which leads to asymmetric loading and degeneration of the joints. Our research will help to offload that excess loading by providing smart assistance to the impaired side and ideally lead to better long term clinical outcomes in this patient population.

What was the impact on other disciplines?

The technology that was researched and developed for this powered prosthesis is of great value to other closely related disciplines. A clear example for this is in PI Young's lab who also work on powered orthoses and robotic exoskeletons. Many of the technologies and techniques that are being developed for this project are being extended by other students to problems in the area of powered orthosis technology. Thus, we foresee the benefits of this study extending beyond powered prostheses and into many wearable robotic systems for human augmentation and assistance of patients with walking disability. For example, we have a project that is already translating some of the technology from this project for a hip exoskeleton, which has an application area in providing assistance for stroke survivors. Thus, we see the technology and other developments of this project extending beyond the amputee patient population and will help in many other kinds of walking disability through translation to wearable robotic systems.

What was the impact on technology transfer?

Nothing to report

What was the impact on society beyond science and technology?

Ultimately, the primary area in which the study is likely to make an impact beyond science and technology is in the area of improving social and economic conditions for persons with amputation. We hope to use this technology to improve mobility outcomes and long-term health outcomes for persons with lower limb amputations. Improving mobility outcomes will likely lead to social improvements through increased community ambulation skills and abilities. Increased community participation increases quality of life and overall health outcomes and is a positive benefit for society. Improving health outcomes will lead to significant economic benefits by reducing the load on the overall health system in treating potentially preventable diseases such as osteoarthritis and osteoporosis that result from asymmetric loading of the lower limbs in patients with amputation, which our technology hopes to address in the future.

5. CHANGES/PROBLEMS:

Changes in approach and reasons for change

Nothing to Report

Actual or anticipated problems or delays and actions or plans to resolve them

As discussed with the Program Manager, we had major lab renovation occurring over the summer and into the fall. Specifically, August and September were heavily affected as the lab was closed during these months. We continued to work on other aspects of the project, but this has put us behind from a data collection stand point. Additionally, we had another shut down to finish renovations for 2 weeks during October. The lab was completely finished in mid-October and has greatly improved clinical and biomechanical functionality that will be utilized heavily for the efforts on this grant. This has delayed the overall progress of the grant, but only from a timeline perspective, which we hope to make back up by requesting a 1-year no cost extension at the end of next year. Notwithstanding these delays, data collection is moving along smoothly with our very active cohort of individuals with transfemoral amputees and we are now moving along nicely.

Changes that had a significant impact on expenditures

Because of delays due to downtime in the lab for renovations, we have delayed spending appropriately to use in the no cost extension period to ensure a successful completion of the project.

Significant changes in use or care of human subjects, vertebrate animals, biohazards, and/or select agents

Significant changes in use or care of human subjects

Nothing to report

Significant changes in use or care of vertebrate animals.

N/A

N/A

6. **PRODUCTS:** List any products resulting from the project during the reporting period. If there is nothing to report under a particular item, state "Nothing to Report."

- **Publications, conference papers, and presentations**
  Journal publications.

A journal paper was submitted to MHSRS Supplement to Military Medicine Update in November 2018. This paper is under review at the moment and will be provided as a supplement in a future report once it is in final form and accepted for publication.

Books or other non-periodical, one-time publications.

Nothing to report

Other publications, conference papers, and presentations.

1) We submitted an abstract in February to the Military Health System Research Symposium (MHSRS) conference. The title of this abstract is: "Powered knee/ankle prostheses for improving walking capabilities in individuals with transfemoral amputation." The authors (in order) are: Aaron Young (PI), Krishan Bhakta, Jonathan Camargo-Leyva, and Lee Childers. This paper was accepted in April as a poster presentation for the August 2018 meeting. Our team presented this work at the MHSRS conference in August and it was received well.

2) We submitted an abstract in February on the project to the 2018 Dynamic Walking conference. This abstract was entitled: "Sensor Fusion for Continuous Walking Speed Estimation on Powered Prostheses." This abstract focuses on using our intent recognition algorithms for walking speed estimation on the prosthesis. We presented this work as a lab at the Dynamic Walking 2018 conference with multiple presentations on the prosthesis project. Dr. Young gave an overview of the lab and project, Jonathan Leyva presented on the sensor fusion machine learning strategy, and Krishan Bhakta presented on the powered prosthesis and the capability of doing real-time walking speed prediction.

3) We submitted two papers on the project to the ASME DSCC conference in October. Both of these are full conference proceedings papers (10 pages) that are available online and indexed. The primary paper on the project was invited to a special session on Bio-Mechatronics and Physical Human Robot Interaction. This paper is entitled: "Control and Experimental Validation of a Powered Knee and Ankle Prosthetic Device." This paper focused on our controls work in getting the device implemented on patients with transfemoral amputation. Krishan Bhakta was the lead author for this paper and presented this work as an oral presentation in October 2018.

4) The second ASME DSCC paper was about a modeling study of impedance parameters for the powered prosthesis. This paper was entitled: "Stochastic Optimization of Impedance Parameters for a Powered Prosthesis Using a 3D Simulation Environment" and was accepted into the regular session. Jonathan Camargo was the lead author for this paper and also presented this work as an oral presentation in October 2018.

5) We submitted a paper to IEEE EMBC in April 2018 (see Appendix D). This paper was accepted for a poster presentation in the July conference in Hawaii. The paper was entitled: "Continuous Walking Speed Estimation using Neural Networks and Multi-Sensor Data Fusion." This paper focused on the machine learning and sensor fusion techniques to estimate walking speed. It was presented at the conference in July 2018.

6) We submitted a conference paper to the 45th Meeting of the American Academy of Orthotists & Prosthetists in July 2018. The authors and title are as follows:*Krishan Bhakta, Jonathan Camargo Leyva, Maximillian Spencer, Brian White, Noah Cho, Kinsey Herrin, Lee Childers, Aaron Young, "Effect of Experimental Powered Prosthesis on Hip Kinetics: A single Case Pilot Study," 45th Meeting of the American Academy of Orthotists & Prosthetists, submitted July 2018. This conference paper discussed some of the initial biomechanical results with the powered leg compared to a passive leg.

- **Website(s) or other Internet site(s)**

http://www.epic.gatech.edu/

This is the lab website which shows the research project, collaborators, funding source, and researchers on the project as well as relevant pictures and descriptions.

Technologies or techniques

We have continued to make improvements to the powered leg to both the mechanical and electronic systems embedded on the device. For mechanical improvements, we have added the functionality of scaling device height to new amputees, improved prosthetic feet capabilities (i.e. left vs. right, traction), and added improved sensors. For the electronics, we have made a compact and lightweight system that has more robust communication, enhanced physical connections via updated printed circuit boards, as well as updated code changes to further enhance our controller's capabilities. We have also developed in-house biomechanics model that incorporates the powered prosthesis in order to simulate/model accurate inverse kinematics and inverse dynamics. We plan to disseminate this technology in future journal articles.

- **Inventions, patent applications, and/or licenses**

Nothing to report

- **Other Products**

Nothing to report

7. PARTICIPANTS & OTHER COLLABORATING ORGANIZATIONS

What individuals have worked on the project?

Name:	*Aaron Young*
Project Role:	*PI*
Researcher Identifier:	
Nearest person month worked:	*6*
Contribution to Project:	*No change*
Name:	*Lee Childers*
Project Role:	*Senior Personnel*
Researcher Identifier:	
Nearest person month worked:	*2*
Contribution to Project:	*No change*
Name:	*Kinsey Herrin*
Project Role:	*Senior Personnel/Supporting Prosthetist*
Researcher Identifier:	
Nearest person month worked:	*2*
Contribution to Project:	*No change*

Name: *Krishan Bhakta*
Project Role: *Graduate Student*
Researcher Identifier:
Nearest person month worked: *27*
Contribution to Project: *No change*

Name: *Jonathan Camargo-Leyva*
Project Role: *Graduate Student*
Researcher Identifier:
Nearest person month worked: *27*
Contribution to Project: *No change*
Funding Support: *Fullbright Fellowship*

Name: *Trent Rankin*
Project Role: *Master's Student*
Researcher Identifier:
Nearest person month worked: *6*
Contribution to Project: *No change*

Name: *Summer Lee*
Project Role: *MSPO Student*
Researcher Identifier:
Nearest person month worked: *1*
Contribution to Project: *No change*

Name: *Brian White*
Project Role: *MSPO Student*
Researcher Identifier:
Nearest person month worked: *2*
Contribution to Project: *Helped to fit amputees to the powered prosthesis.*

Name: *Maximillian Spencer*
Project Role: *MSPO Student*
Researcher Identifier:
Nearest person month worked: *2*
Contribution to Project: *Helped to fit amputees to the powered prosthesis.*

Name: *Meghan O'Malley*
Project Role: *Emory PT Student*
Researcher Identifier:
Nearest person month worked: *1*
Contribution to Project: *Help with biomechanics analysis with prosthesis*

Name: *Alanna Dyko*
Project Role: *Emory PT Student*
Researcher Identifier:
Nearest person month worked: *1*
Contribution to Project: *Help with biomechanics analysis with prosthesis*

Name: *Aiden Yoon*
Project Role: *Emory PT Student*
Researcher Identifier:
Nearest person month worked: *1*
Contribution to Project: *Help with biomechanics analysis with prosthesis*

Name: *Phillip Kellogg*
Project Role: *Emory PT Student*
Researcher Identifier:
Nearest person month worked: *1*
Contribution to Project: *Help with biomechanics analysis with prosthesis*

Name: *Maegan Tucker*
Project Role: *Undergraduate Researcher*
Researcher Identifier:
Nearest person month worked: *3*
Contribution to Project: *No change*
Funding Support: *PURA Fellowship*

Name: *Noel Csomay-Shanklin*
Project Role: *Undergraduate Researcher*
Researcher Identifier:
Nearest person month worked: *2*
Contribution to Project: *No change*
Funding Support: *PURA Fellowship*

Name: *Will Flanagan*
Project Role: *Undergraduate Researcher*
Researcher Identifier:
Nearest person month worked: *3*
Contribution to Project: *No change*
Funding Support: *PURA Fellowship*

Name: *Lance Lu*
Project Role: *Undergraduate Researcher*
Researcher Identifier:
Nearest person month worked: *2*
Contribution to Project: *No change*

Name: *Achint Lehal*
Project Role: *Undergraduate Researcher*
Researcher Identifier:
Nearest person month worked: *2*
Contribution to Project: *No change*

Name: *Aria Amthor*
Project Role: *Undergraduate Researcher*
Researcher Identifier:
Nearest person month worked: *3*
Contribution to Project: *No change*

Name: *Jared Li*
Project Role: *Undergraduate Researcher*
Researcher Identifier:
Nearest person month worked: *5*
Contribution to Project: *No change*

Name: *Sarah Violante*
Project Role: *Undergraduate Researcher*
Researcher Identifier:
Nearest person month worked: *1*
Contribution to Project: *No change*

Name: *Kevin Edwards*
Project Role: *Undergraduate Researcher*
Researcher Identifier:
Nearest person month worked: *2*
Contribution to Project: *No change*

Name: *Vaun Clagett*
Project Role: *Undergraduate Researcher*
Researcher Identifier:
Nearest person month worked: *1*
Contribution to Project: *No change*

Name: *Cory Stine*
Project Role: *Undergraduate Researcher*
Researcher Identifier:
Nearest person month worked: *1*
Contribution to Project: *No change*

Name: *Noah Cho*
Project Role: *Undergraduate Researcher*
Researcher Identifier:
Nearest person month worked: *6*
Contribution to Project: *No change*

Name:	*Pratik Kunapuli*
Project Role:	*Undergraduate Researcher*
Researcher Identifier:	
Nearest person month worked:	*5*
Contribution to Project:	*No change*
Name:	*Stephen Mock*
Project Role:	*Undergraduate Researcher*
Researcher Identifier:	
Nearest person month worked:	*1*
Contribution to Project:	*No change*
Name:	*Ji Bok*
Project Role:	*Undergraduate Researcher*
Researcher Identifier:	
Nearest person month worked:	*5*
Contribution to Project:	*No change*
Name:	*Daniel de Matheu*
Project Role:	*Undergraduate Researcher*
Researcher Identifier:	
Nearest person month worked:	*4*
Contribution to Project:	*No change*
Name:	*Divya Chowbey*
Project Role:	*NSF SURE Robotics Program Undergraduate Researcher*
Researcher Identifier:	
Nearest person month worked:	*2*
Contribution to Project:	*No change*
Name:	*Darren Maguire*
Project Role:	*Undergraduate Researcher*
Researcher Identifier:	
Nearest person month worked:	*2*
Contribution to Project:	*No change*
Name:	*Jaeyoon Kim*
Project Role:	*Undergraduate Researcher*
Researcher Identifier:	
Nearest person month worked:	*2*
Contribution to Project:	*No change*
Name:	*Christian Croxton*
Project Role:	*Undergraduate Researcher*
Researcher Identifier:	
Nearest person month worked:	*1*
Contribution to Project:	*No change*

Name:	*Dylan Nektalov*
Project Role:	*Undergraduate Researcher*
Researcher Identifier:	
Nearest person month worked:	*1*
Contribution to Project:	*No change*

Has there been a change in the active other support of the PD/PI(s) or senior/key personnel since the last reporting period?

During Year 2, Ms. Kinsey Herrin took over as lead clinician and prosthetist on this grant. She has taken over the role of recruiting subjects, bringing them in, fitting them to the device and performing prosthetic alignment. She largely took over Lee Childers role in this aspect. Lee has continued to serve as a consultant on the project and has actively been monitoring data and publications as a result of this work and helping with manuscript preparation. These changes have been positive and clinical support on the project is proceeding well.

What other organizations were involved as partners?

Organization Name: CalTech
Location of Organization: Pasadena, California
Partner's contribution to the project: Collaboration. Specifically, Dr. Ames, who was originally a collaborator at Georgia Tech left his position here to go to CalTech. He and his group have continued to collaborate on the project, specifically the design of the prosthetic leg throughout the grant.

8. SPECIAL REPORTING REQUIREMENTS

COLLABORATIVE AWARDS: N/A

QUAD CHARTS: Attached as a separate document

9. APPENDICES: Quad Chart

Appendix A: Military Health System Research Symposium (MHSRS) Abstract

Appendix B: ASME DSCC Conference Paper #1

Appendix C: ASME DSCC Conference Paper #2

Appendix D: IEEE EMBC 2018

Appendix E: 45th Meeting of the American Academy of Orthotists & Prosthetists

Appendix F: Prosthetic Survey

Appendix A: Military Health System Research Symposium (MHSRS) Abstract

Title: Powered knee/ankle prostheses for improving walking capabilities in individuals with transfemoral amputation

Authors: Aaron Young, Krishan Bhakta, Jonathan Camargo-Leyva, and Lee Childers

Date of Conference: August 20th – 23rd 2018

Location of Conference: Kissimmee, Florida

Title: Powered knee/ankle prostheses for improving walking capabilities in individuals with transfemoral amputation

Background: Powered prostheses are a promising new technology that may help people with lower limb loss to improve function. These individuals suffer from significantly impaired mobility that results in up to 60% more energy than non-amputee individuals. To improve mobility in prosthesis users with a transfemoral amputation, our multidisciplinary Team spanning across investigators at Georgia Tech, the Center for the Intrepid and California Institute of Technology have been developing a new state-of-the-art prosthesis that actively generates mechanical power at the knee and ankle joints. A challenge with powered multi-joint prosthetic systems has always been the integration of a sensor suite with a control system that can recognize different tasks and environments the person is walking in, and then respond accordingly. The human user adds another layer of complexity. This person has lost a large portion of their motor system and must interact with the device via the soft tissues of their residual limb inside the prosthetic socket. The person will also be responding to their environment and with an intent to move a certain way. The powered prosthesis is not directly attached to the user's motor system and must infer, indirectly, the intent of the user within the context of the environment and then aid the user in the movement task. We have taken a systematic approach to developing this powered prosthesis and control system by first starting with a well-defined task where the intent of the user is known before progressing to more complex tasks. The purpose of this initial study was to test the ability of the control system in conjuction with our new powered prosthesis to integrate with the user during steady state walking on a treadmill. We defined success for this stage of develop as a prosthesis that can, (1) correctly recognize the different phases of gait, (2) tune joint impedance to scale across a range of gait speeds, (3) generate knee and ankle kinematics similar to intact walking. These results will then inform device development and enable further development that will allow for other tasks such as traversing stairs and slopes and performing transitions between sitting, standing and walking.

Methods:

Powered Prosthesis Device: The new knee/ankle powered prosthesis that we have designed has a number of novel features including two series elastic actuators that allow for high accuracy torque sensing and control at both the knee and ankle joints. The ankle joint has two degrees-of-freedom (DoF) including a powered dorsi/plantar flexion DoF and a passive, compliant DoF for inversion/eversion function. The knee joint has one DoF for flexion/extension. Each degree-of-freedom (3 total) is equipped with an absolute encoder to measure position and velocity information of joint rotation. The device weighs approximately 7.5 kg, can accommodate build heights of 46 cm to 63 cm, and can deliver up to 72 Nm of continuous torque at the knee and 105 Nm at the ankle. The device is a fourth generation design built in collaboration with Dr. Aaron Ames lab at the California Institute of Technology.

Control System: The device used a finite state machine in conjunction with impedance control to modulate device assistance. The finite state machine was broken into four states for walking: early/mid stance, late stance, swing phase flexion and swing phase extension. Thresholds placed on mechanical sensors were used to switch between states in the state machine. Impedance control laws were used within each state which set a virtual spring and damper. Mechanical power was injected into the system by changing the equilibrium point of the virtual spring during state changed. This control strategy allowed for key properties of the gait cycle to be controlled including powered plantarflexion during push-off, powered knee flexion swing initiation, powered knee extension assistance, and stiffening of the knee and ankle for breaking during early to mid-stance.

Experimental Design: Three individuals with transfemoral amputation (age 58, 36, 51; weight [kg] 95.2, 93.9, 74.8; height[m] 1.80, 1.80, 1.82) were recruited and provided informed consent for this IRB protocol approved by the Georgia Institute of Technology. The shank height of the device was adjusted to align the knee center of rotation with the patient's biological knee center. The device was fitted and aligned by a certified prosthetist and the patient walked in a set of parallel bars overground while learning to walk with powered assistance. Control parameters and prosthetic alignment were tuned during this time to ensure comfortable transfer of power during walking and minimization of clinical gait deviations. This adjustment period typically took 30-45 minutes per subject. After each patient was comfortable walking with the device, they proceeded to walking on a treadmill. We analyzed the biomechanics of walking using the outputs from sensors in the prosthesis at a range of speeds of six different speeds evenly spaced between 0.6 m/s to 1.1 m/s. Each patient walked for 1 minute in each of the six conditions. Outcome measures included kinematics and kinetics of the knee and ankle, accuracy of the state machine in recognizing phase changes, and subjective patient evaluations.

Results:

The tuning performed while the participant walked in the parallel bars was sufficient to obtain steady state walking across the range of speeds on the treadmill. This was evident in that each user was able to achieve stable and comfortable walking without the research Team having to manually change parameters during the experimental conditions on the treadmill.

Our phase estimation accuracy using the state machine was extremely robust. Each patient took between 200-300 steps for a total of 748 prosthesis steps overall which resulted in 2992 phase transitions during walking on the treadmill. The state machine was able to recognize these with 100% accuracy and never failed to transition or transition too early. Knee kinematics closely followed able-bodied data with a peak knee angle of ~60 degrees during swing flexion. The knee remained generally extended throughout the stance phase in these participants, with an average of 0.31° and 0.14° standard deviation of knee flexion. This is contrary to normal gait that has ~ 20 degrees of stance phase knee flexion. However, none of the patients felt comfortable when this was allowed during tuning and so it was tuned out of the device for the experiment. Ankle angle profiles also closely followed biological patterns across subjects and the prosthesis demonstrated ankle plantarflexion during initial swing leading to ankle dorsiflexion during mid-swing. Both knee and ankle angle profiles were relatively invariant across walking speeds. Ankle torques followed a biological pattern and increased during push-off for powered plantarflexion assistance as a function of walking speed. Knee torques were invariant as a function of walking speed.

Conclusions:

This new powered knee/ankle prosthesis was able to generate reliable walking gait across a wide range of walking speeds for individuals with a transfemoral amputation. The control system was able to correctly identify the phase of gait, set the correct gait phase specific impedance, and generate near normal lower limb kinematics. The lack of knee flexion during stance phase was intentional due to user preference, not the capability of the prosthesis. This may be because motion inherit in the limb/socket interface may allow for the impact absorption normally handled by knee flexion or the users did not employ knee flexion strategies during stance in their own prostheses and were not trained to use it in our prosthesis. Future research will extend this work by providing biomimetic assistance for ramps and stairs.

Appendix B: ASME DSCC Conference Paper #1
Title: Control and Experimental Validation of a Powered Knee and Ankle Prosthetic Device
Authors: Krishan Bhakta, Jonathan Camargo, Aaron J Young
Date of Conference: September 30th – October 3rd 2018
Session Title: Bio-Mechatronics and Physical Human Robot Interaction
Location of Conference: Atlanta, Georgia

Proceedings of the ASME 2018 Dynamic Systems and Control Conference
DSCC2018
September 30-October 3, 2018, Atlanta, Georgia, USA

DSCC2018-9218

CONTROL AND EXPERIMENTAL VALIDATION OF A POWERED KNEE AND ANKLE PROSTHETIC DEVICE

Krishan Bhakta
Georgia Institute of Technology
Department of Mechanical Engineering
Atlanta, GA, 30332, USA
kbhakta3@gatech.edu

Jonathan Camargo
Georgia Institute of Technology
Department of Mechanical Engineering
Atlanta, GA, 30332, USA
jon-cama@gatech.edu

Aaron J Young
Georgia Institute of Technology
Department of Mechanical Engineering
Atlanta, GA, 30332, USA
aaron.young@me.gatech.edu

ABSTRACT

Developing active prostheses require robust design methodologies and smart controllers in order to appropriately provide net positive mechanical work to the user. Passive prostheses are limited in their ability to sustain walking for long periods of time as well as ambulating over different terrains/environmental conditions. In this paper we present a control architecture and validation results on three individuals with transfemoral amputation using our powered knee and ankle prosthetic device. A three stage controller structure is proposed: high-level control, mid-level control, and low-level control. The high-level controller is responsible for determining the locomotion mode. At the mid-level control, an impedance controller is paired with a state machine to coordinate the kinematics and kinetics of the device with the user during community ambulation tasks. At the low-level control, the device is paired in conjunction with a series elastic actuator (SEA) at each joint to enable closed-loop torque control (PID control). Our results indicate that our powered prosthetic device is capable of scaling to a range of speeds without having to tune many impedance parameters. Our approach shows that our device is a good platform for further testing robust controllers that can provide powered assistance to the user.

1 INTRODUCTION

Transfemoral amputation is a significant cause of disability in the United States, the expected number of people to have limb loss will have doubled by the year 2050 [1]. Passive prostheses lack the ability to generate net power at both the knee and ankle joints which limits the capabilities of a user to ambulate freely. Transfemoral amputees walking with passive prostheses have been shown to expend 60% more metabolic energy compared to healthy subjects during level walking [2]. Hence developing a prosthesis that is able to deliver the appropriate power and mechanical torque is necessary for improving quality of life for users. Additionally, with on-board mechanical sensors, active prostheses have the potential to assist people in a variety of locomotion tasks besides just level-walking [3].

Existing devices on the market including iWalk's BiOM [4,5], Ossur's Power Knee [6], and Ottobock's C-Leg [7] may help overcome some of the limitations seen in passive prostheses. Even though these devices are able to help amputees ambulate better, there are still limited approaches of handling different modes of locomotion. Current methods include compensatory movement of the leg or physical contact with a switch to transition between modes which is burdensome to the user [8]. Ideally, a device should be able to help provide smooth natural transitions between locomotion modes as well as reduce the time spent on the intact limb [9].

However, there are still many challenges involved in making a device optimal for the user such as mechanical design, selection of electronics, and hardware/software integration. Our prosthetic device currently uses an impedance based controller which allows the user to dynamically interact with the environment, rather than adhering to kinematic trajectories [10–13]. The design utilizes a set of series elastic actuators (SEA) for executing closed loop control via measured feedback. A three stage control scheme is proposed to help the user ambulate over common walking tasks. A variety of mechanical sensors (encoders, IMU's, and 6-axis loadcell) and actuators are embedded on the system in order to capture sensor information and provide appropriate powered assistance. The on-board sensing and control architecture are presented to give a complete design overview. Finally, the device and controller architecture was validated by testing on two able-bodied subjects and three transfemoral amputees walking at a wide range of walking speeds.

2 MECHANICAL DESIGN

An updated design was developed based off of AMPRO3 [14] from a collaboration between the EPIC (Exoskeleton and Prosthetic Intelligent Controls) lab at Georgia Tech and the AMBER (Advanced Mechanical Bipedal Experimental Robotics) lab at CalTech. The device is a powered knee and ankle device that has one actuated DOF at the knee joint in the sagittal plane, and 2 DOF's at the ankle which consist of an actuated plantarflexion and dorsiflexion DOF and a passive inversion and eversion DOF.

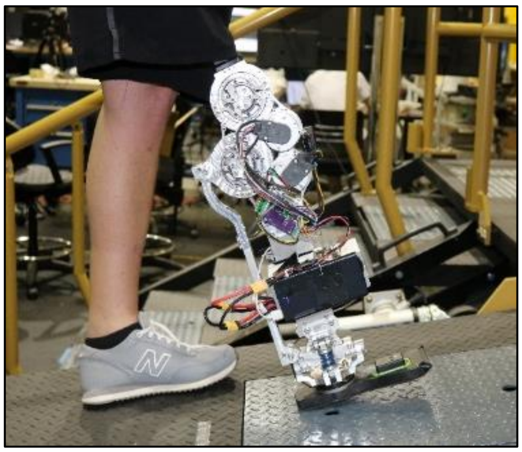


Figure 1: Overview of the knee-ankle prosthetic device. A 37V battery is used to power the actuators, while a portable battery power bank is used for the microprocessor.

The device weighs approximately 8 kg (including battery) and is more customizable by having the ability to change heights. The device has a knee adapter component that allows for testing with able-bodied subjects through a pin joint system, while a pyramid connector can be mounted on top to connect directly with an amputee's socket configuration. Both knee and ankle joints are actively controlled using two 206 W brushless DC motors (MOOG BN23) which are capable of achieving approximately 1 N-m peak torque [1]. In order to reach human biological torque capabilities, the device utilizes a gear transmission ratio of 1:175 at the ankle joint and 1:120 at the knee joint. The gearbox consists of a harmonic drive (CSG-17-100-2UH-LW) that reaches a 1:100 reduction and a variable pulley-belt system that produces the remaining gear reductions for both joints. The following table shows the device specs based on an efficiency of 70% [14].

Table 1: Device Specifications

Joint	Knee	Ankle
Peak Torque	84 Nm	122.5 Nm
Continuous Torque	26.5 Nm	38.5 Nm
Max Angular Velocity	5.8 rad/s	4.0 rad/s
Range of Motion	0-70 deg (Sagittal)	-25 to 40 deg (Sagittal) Passive Springs (Frontal)

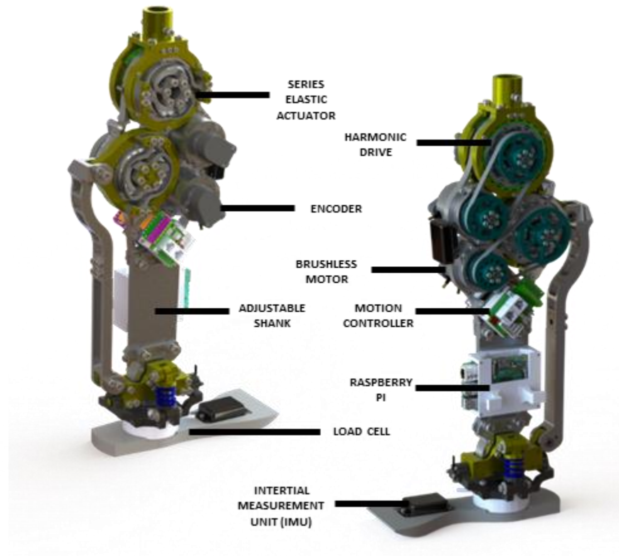


Figure 2: Features of the device including: SEA's (top left), harmonic drive (top right), encoders (middle left), motors and motor controller (middle right), microprocessor (middle right), 6-DOF load cell (bottom left), and IMU's (bottom right).

The height adjustment linkages and inserts allow for matching sound-side knee joint centers of persons with transfemoral amputation. The process of measuring the knee joint center and configuring the device to fit properly with the user came under the instruction of a certified prosthetist at the Masters of Science in Prosthetics and Orthotics (MSPO) program at Georgia Tech. To measure the knee joint center, one must locate the tibial plateau and the femoral condyle and find the mid-point between these two anatomical locations on the sound side limb. To ensure that the fit is correct and achieve good biomechanics, the biological knee joint and the prosthetic knee joint rotation must be aligned while the person is walking. The ability of our device to be adjusted for different height conditions allows the user to feel more stable and prevent the user from having gait deviations from abnormal height differences during walking tasks. The device height is able to range from 40.6 cm to 57.5 cm in fixed increments to accommodate a large range of users including using an able-bodied adapter.

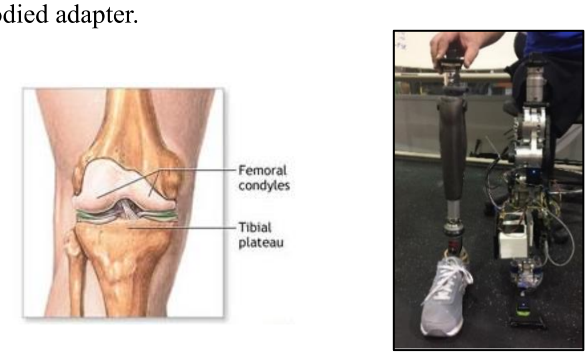


Figure 3: Diagram of knee joint center (left) [15]. Device height validation and knee joint center alignment with user's passive prosthetic setup (right).

The shape of the series elastic actuator (SEA) joints were based off a design seen in [14,16]. The material chosen for the torsional spring was maraging 300 steel (Service Steel Aerospace). Finite element analysis (FEA) was performed in SolidWorks to model the torsional spring stiffness. The desired stiffness in [14] was designed to reach 20 Nm/deg.

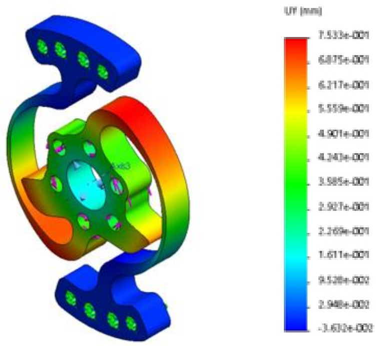


Figure 4: FEA displacement results on M300 steel under 50 N*m static torque condition.

FEA yielded similar results at 18.34 ± .05 Nm/deg. The analysis was performed under the following conditions. All of the holes seen in the torsional spring design were statically fixed to emulate mounting position on the prosthetic device. The simulated torque varied from 10-50 Nm to match device continuous torque capabilities in order to create a torque-displacement figure where the torsional spring stiffness value was found by fitting a linear best fit line. Experimental testing was performed with Instron axial-torsion machine where an axial force was applied to a custom rig that allowed for translating the axial force to a torque via a known length lever arm. The experiment was performed under different force conditions to confirm whether the spring acted linearly under repeated loading. A linear regression model was fit to the experimental data where the knee torsional spring was found to be 12.463 Nm/deg ($R^2 = .993$) and the ankle torsional spring was found to be 10.632 Nm/deg ($R^2 = .981$).

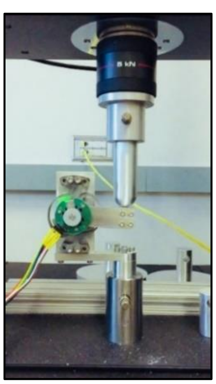


Figure 5: Testing of torsional spring. An absolute encoder (green sensor) is mounted on the axis of the spring to measure the spring deflection. An axial force from the Instron is applied to a level arm in order to generate a torque about the spring.

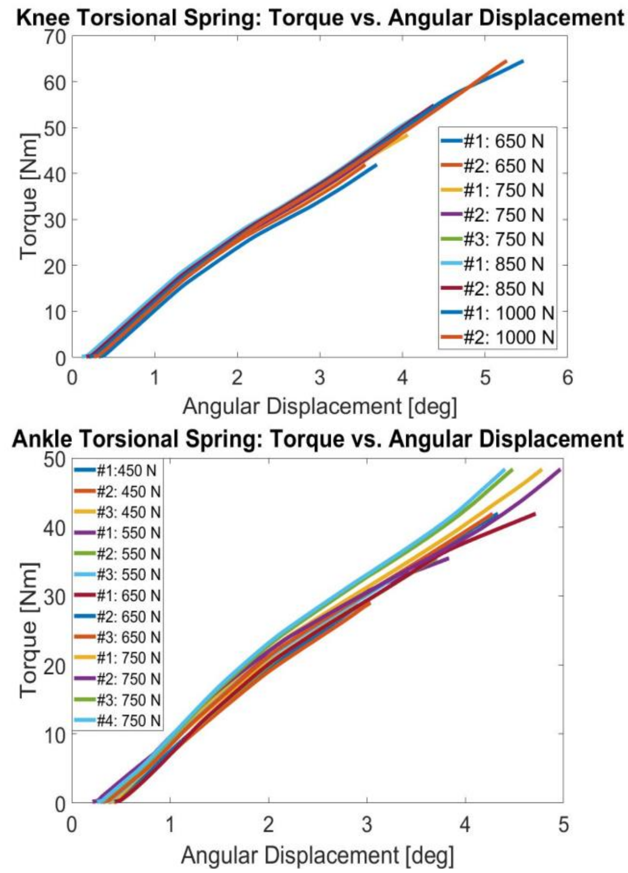


Figure 6: Experimental data of torque versus angular displacement for both knee and ankle joints. A linear regression is fit to the experimental data to extrapolate the stiffness value for each torsional spring.

Passive prostheses use certain types of feet that allow a user to have better control when supporting their own body weight as well as providing some return of elastic energy [17]. The foot design on our prosthetic device was created to have more advantageous effects as mentioned in [18]. Due to design constraints of keeping a compact design profile, the foot has a radius of curvature of approximately 93.5 mm at the forefoot. This helps the user to smoothly transition from step to step that occurs at push off. After preliminary testing, we found that the foot was poor at providing good heel contact and push-off biomechanics. A heel was added to allow for better plantar-flexor control. Two feet were manufactured out of nylon to allow for users to wear the device on either side depending on their affected limb. The dimensions of the each foot is approximately 236.03 mm by 88.46 mm (length x width). The design also includes mounting holes for where the load cell and an IMU can be placed for sensor feedback of the foot kinematics.

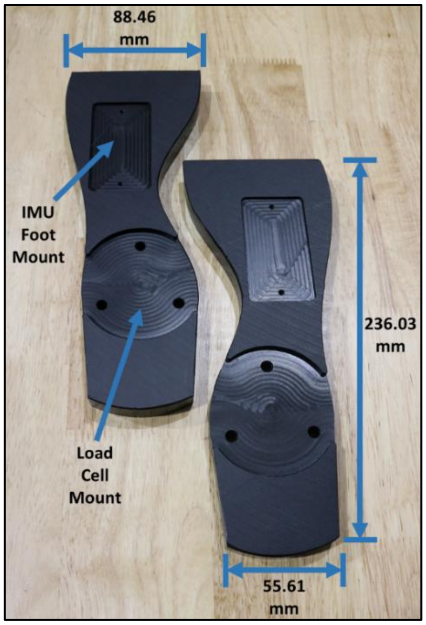


Figure 7: Nylon foot design of the prosthetic device

3 ELECTRONICS

A Raspberry Pi 3 Model B microprocessor (4x ARM Cortex-A53, 1.2 GHz) runs the control architecture of the device. It is responsible for gathering sensor information and performing any computation on board the device. The low-level control of outputting motor torques comes from using two gold solo whistle ELMO motion controllers (G-SOLWHI20/100SE). The motion controllers are responsible for reading the two encoders at each joint – an incremental encoder (US Digital E5) on the input side of the motor and an absolute encoder (Renishaw RM22) on the output side of the joint which can measure the spring deflection of the torsion spring. The Raspberry Pi is also able to record sensor information from 3 inertial measurement units (IMU's, YOST 3-Space USB) which are fixed to the foot and shank on the device and attached to the thigh of the user. Furthermore, a 6-DOF load cell (SRI M3714C2) is incorporated in the foot design of the device.

To ensure the functionality of the Raspberry Pi is optimal, a custom printed circuit board (PCB) was designed for attaching to the ELMO motion controller as well as incorporating an off the shelf CAN bus shield for communication purposes. The PCB allows for the Raspberry Pi to communicate with the ELMO motion controllers and load cell simultaneously through CAN bus communication protocols. The Raspberry Pi also allows for the IMU's to be integrated with available USB ports. The result of this implementation is the ability for all the electronics to be onboard the device and used in real-time by the microprocessor. The whole system is powered through a 10-cell battery (37 V), a 3600 mAh Li-Po battery (Venom Power) and a portable power bank for the Raspberry Pi. The electrical components and sensors are shown in Fig. 2. All of the controls on the device are coded in C++ packages that run on the robot operating system (ROS) platform. An accompanying GUI capable for relaying live signals was coded using Python packages.

4 CONTROL DESIGN

4.1 HIGH-LEVEL CONTROL

Determining which locomotion mode a user is in is the responsibility of the high level controller. This allows for the user to ambulate across a variety of walking tasks such as level-ground walking, ramp ascent/descent, and stair ascent/descent. The high level controller is implemented on the microprocessor which handles sensor inputs and converts to walking mode outputs. These outputs are determined by using sensor fusion techniques and machine learning algorithms to better adapt to the user. The details of the high level control and validation are not a focus of this paper, but prior work can be found in literature[19–22].

4.2 MID-LEVEL CONTROL

The device is controlled using an impedance based model that generates torque commands (τ), for both the knee and ankle joints via Eq. (1):

$$\tau_i = -k_i(\theta_i - \theta_{e,i}) - b\dot{\theta}_i \qquad (1)$$

where i relates to the joint, θ relates to the joint angle, $\dot{\theta}$ relates to the joint angular velocity. The positive values correspond to knee flexion and ankle dorsiflexion, while negative values correspond to knee extension and ankle plantarflexion. The three virtual impedance parameters of each joint were stiffness, k, equilibrium angle, θ_e, and damping coefficient, b. The impedance controller was implemented in conjunction with a finite state machine, which modified these impedance parameters in order to provide appropriate torque control in each phase. The finite state machine was divided into four states. The stance phase was divided into early stance and late stance, while the swing phase was divided into swing flexion and swing extension. Transitions between states were triggered through embedded mechanical sensors on the prosthetic device. In Fig. 8, T1 refers the ankle angle threshold to transition from early stance to late stance, T2 refers to the load cell force in the z-direction to be lower than a threshold to transition between late stance and swing flexion, T3 refers to the knee velocity threshold to transition between swing flexion to swing extension, and T4 refers to the load cell force in the z-direction to be greater than a threshold to transition between swing extension back to early stance.

4.3 LOW-LEVEL CONTROL

This device is capable of providing torque feedback compared to other available powered prostheses. The torque desired outputted by the mid-level control is transformed to a current that is sent to the device. The actual torque from the SEA's is calculated via Eq. (2) where k is the stiffness of the torsional spring and θ is the angular deflection of the spring. A PID control loop is used to minimize the error between the desired and actual torque.

$$\tau_{actual} = k * \theta_{spring} \qquad (2)$$

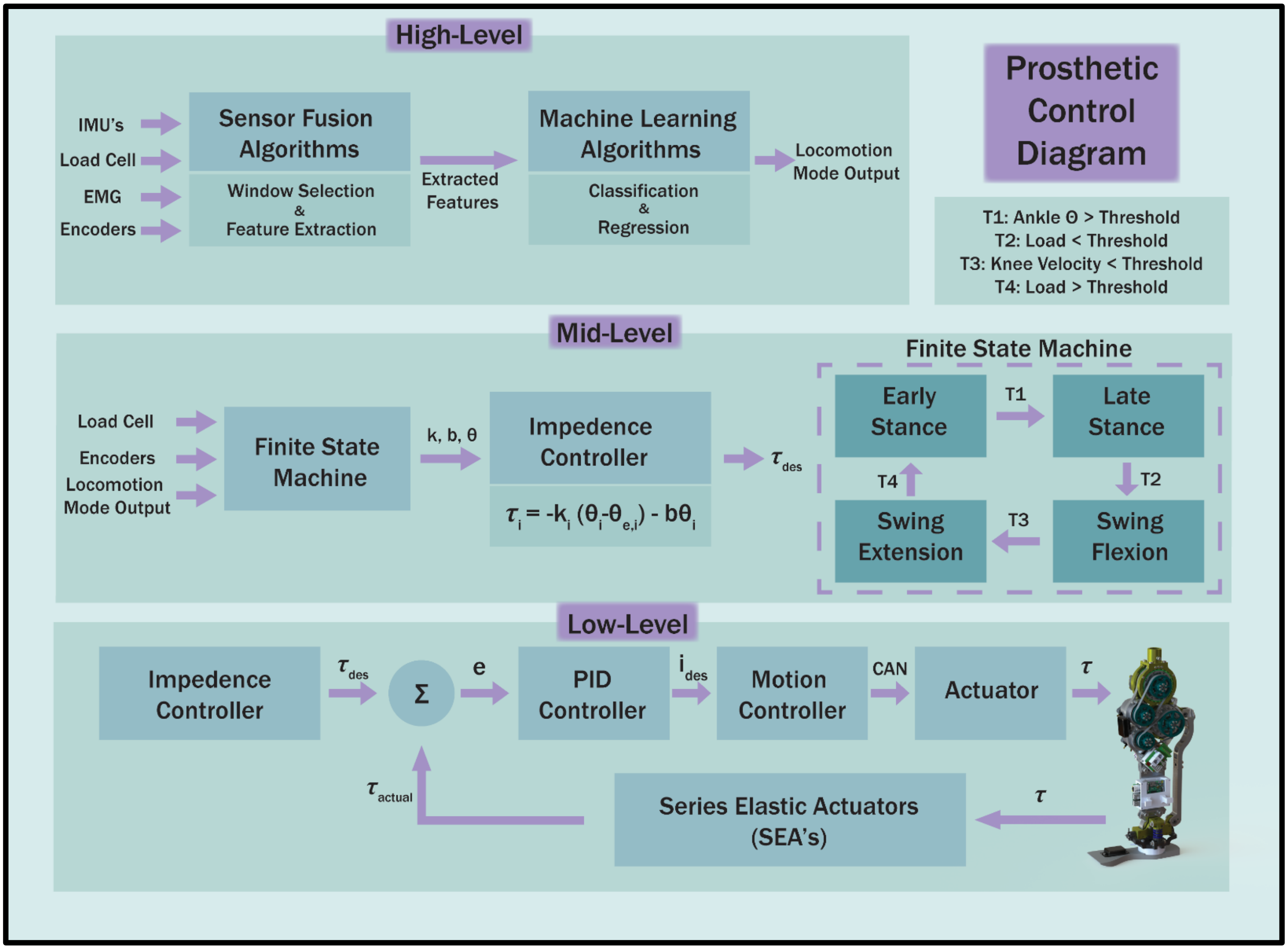


Figure 8: Prosthetic control architecture diagram. High-level controller that determines what locomotion mode the user is in via sensor fusion techniques (top). Mid-level controller that uses an impedance controller and finite state machine to generate desired torques (middle). Low-level controller that runs closed loop control with torque feedback from the Series Elastic Actuators (bottom).

5 DEVICE VALIDATION

The device was validated by running through several benchmarks of testing. Our validation for this paper focused exclusively on the mid-level controller. The low level controller only commanded the torque from the mid-level layer and did not correct based on feedback from the series elastic actuators. All testing was done in level-walking and thus intent recognition performed in the high-level layer was not needed for these validations results. First, the device underwent a series of tests to determine the communication protocols and electronic hardware required to communicate to all of the sensors and test the torque inputs versus the dynamics of the device. Human subject testing included two able bodied subjects and three subjects with transfemoral amputation.

5.1 METHODS

Benchtop Testing

The device was fixed to a frame as seen in Fig. 9 at the knee adapter component where there was no ground contact. Several tests were conducted in order to determine torque-angle relationships for both joints. The torque versus angle dynamics were controlled by the impedance control law seen in Eq. 1 through open-loop control but with the damping coefficient set to zero. The knee torque-angle relationship as seen in Fig. 10 was generated by having the user set the initial position of the knee joint at maximum extension ($\theta = 0°$) and having a torque input that would cause knee to flex a certain amount. The ankle torque-angle relationship also seen in Fig. 10 was generated by having the user set the initial position of the ankle at maximum plantarflexion ($\theta = -25°$) and creating a torque input that dorsi-flexes the ankle up.

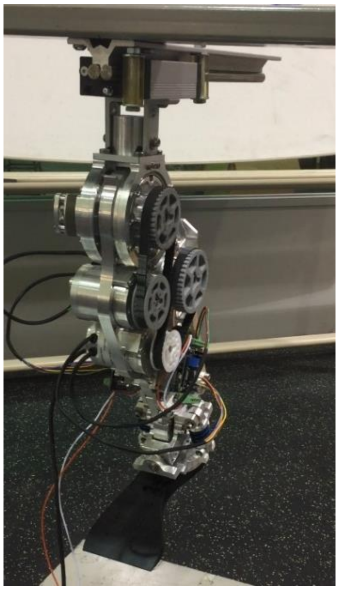


Figure 9: Experimental test setup for benchtop testing

Able-bodied testing

First experimental protocols of walking with the device were performed by able-bodied subjects by using a modified iWALK adapter at the knee. All subjects gave written, informed consent on the approved protocol by the Georgia Institute of Technology. AB01 and AB02 were 20 and 21 years old, respective weights were 81.65 kg, and 88.45 kg, and heights were 1.85 m and 1.75 m. An adjustable platform shoe was appropriately fitted to help the user balance due to the introduced height difference by the adapter. Users were asked to ambulate at preferred walking speeds on a treadmill and told to rely minimally on the parallel bars (primarily used for balance). Starting parameters were taken from [23].

Amputee Testing

3 subjects (TF01, TF02, and TF03) with unilateral transfemoral amputations completed the experimental protocol, which was approved by the Georgia Institute of Technology Institutional Review Board. All subjects gave written, informed consent on the approved protocol. Subject's ages were 58, 36, 51 years old, weights were 102.06 kg, 99.79 kg, 74.84 kg, and heights 1.80 m, 1.83 m, 1.80 m. All subjects were community ambulators (K3 and above). The prosthetic device was configured to the user under the supervision of a certified prosthetist. Baseline impedance parameters were taken from [23] for tuning the controller for level-ground walking. Constant values were used and tuned to each subject appropriately until they felt comfortable walking with the device and met some common ambulation goals suggested by the prosthetist. Parameters were configured for each user by performing a visual inspection of the kinematics and feedback for the prosthetist and user. The prosthetist observed the user's gait in both the sagittal and frontal plane and appropriately adjusted the socket to device connection to improve their gait as well as letting the operator know what needed to be improved. The operator would adjust the impedance parameters in order to match the feedback received by the user and prosthetist. A parameter sweep of impedance parameters was performed until the user and prosthetist were satisfied with the user's performance. Each session began with the users walking inside a set of parallel bards until they were comfortable with the device. The next step was to let the users walk on a treadmill at their preferred walking speed with the device. For each trial and tuning process, a gait belt harness was utilized to ensure user safety during walking. Impedance parameters were recorded with any changes compared to the default values for every user. After users were tuned and ensuring minimal weight acceptance on the parallel bars, kinematic and kinetic data was collected as well as IMU and loadcell data.

A second session of data collection was performed with variable walking speeds for one minute for each respective speed. The range of speeds tested were 0.63 m/s, 0.72 m/s, 0.80 m/s, 0.89 m/s, 0.98 m/s, and to 1.07 m/s. The default parameters were the same ones used from the first session of data collection with minor changes in tuning parameters. Similarly, the amputees were asked to walk over parallel bars before walking on the treadmill. Two of the three individuals with amputation were brought back for this session.

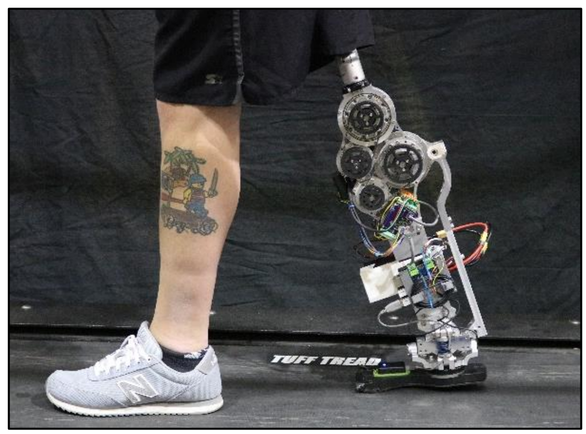


Figure 10: Transfemoral amputee (TF02) walking on treadmill at different speeds (level-walking).

5.2 DATA ANALYSIS

Data was recorded using the data-logging capabilities provided through the ROS platform (rosbag record) for all the sensors embedded on the device. The rosbag data was then post-processed which included segmentation and normalization using the early stance state from the mid-level control which emulates the heel strike to heel strike behavior seen in the gait cycle. Average kinematic and kinetic data of approximately 40 strides per trial was then plotted for able-bodied individuals and amputees. Data was then compared to literature values seen in [24].

5.3 RESULTS

Benchtop Testing

Figure 11 shows the desired torque outputted by the impedance controller under different stiffness conditions for the knee and ankle joints. The behavior from the knee joint and ankle joints show that there is a linear relationship of the torque versus angle for a certain range of motion when using the open-loop control methodology.

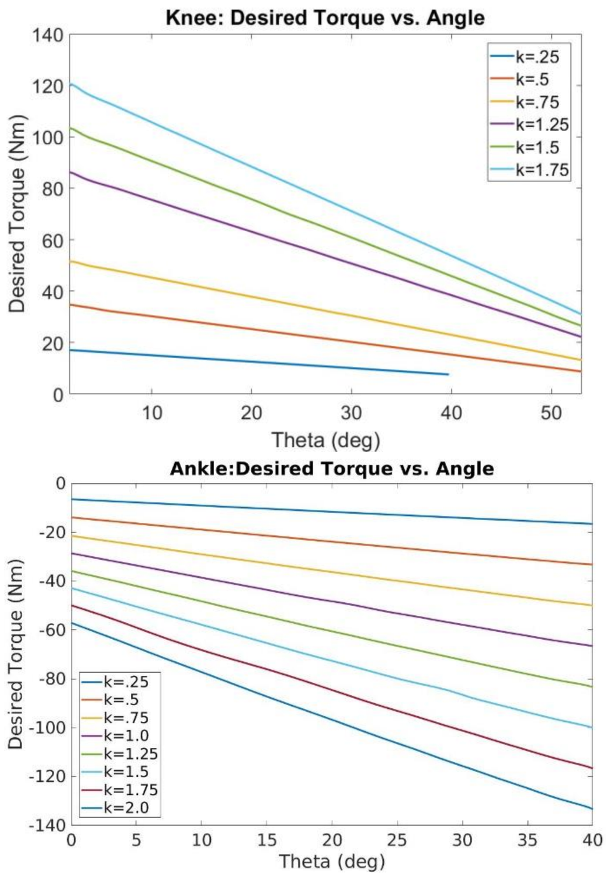


Figure 11: Desired knee torque versus knee angle at different impedance stiffness values (top). Desired ankle torque versus ankle angle at different impedance stiffness values (bottom).

Able-bodied testing

Users, regardless of experience level were able to walk with the device with constant impedance parameters. Minor changes of tuning parameters were made to improve joint kinematics and user comfort. Figure 12 shows the average kinematic and kinetic profiles from the device while an able-bodied user (AB01) ambulated on a treadmill at their preferred walking of 0.9 m/s. Table 2 shows the constant parameters and transition thresholds as the user was walking with the device. The peak plantarflexion angle seen was -12.72 degrees, while the peak knee flexion angle was 61.73 degrees. The maximum plantarflexion torque reached was -1.08 Nm/kg, while he maximum knee extension torque was -0.76 Nm/kg.

Amputee Testing

Figure 13 shows the kinematic data of users walking at their preferred speed (~0.90 m/s). Only 6 impedance parameters and 3 trigger thresholds across all 3 amputee users needed to be tuned which are bolded in Table 2.

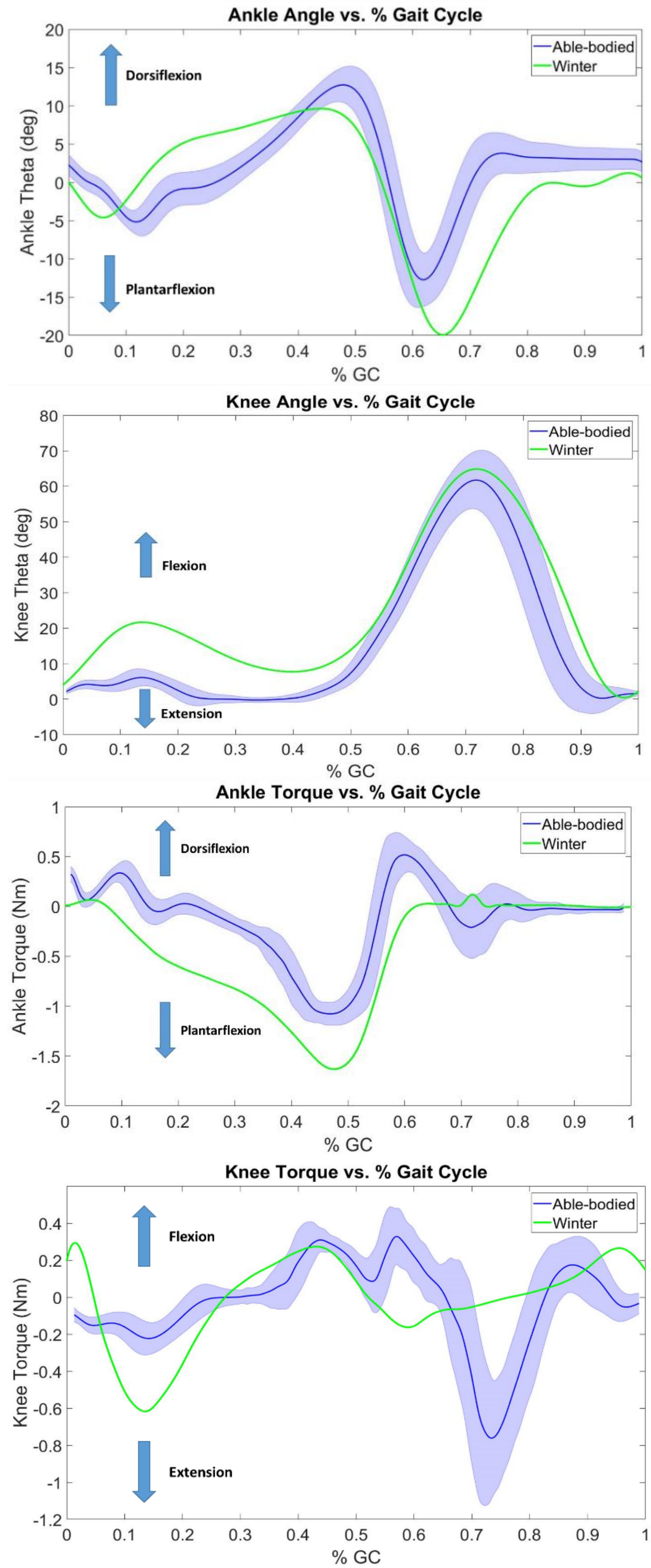


Figure 12: AB01 average kinematic and kinetic data across 40 strides of both the knee and ankle joints compared to healthy biomechanics data [24].

Table 2: Impedance Parameters for able-bodied individuals and amputees

Subject	Phase	Knee Parameters			Ankle Parameters			Trigger Thresholds			
		k (Nm/deg)	b (Ns/deg)	θ (deg)	k (Nm/deg)	b (Ns/deg)	θ (deg)	T1 (deg)	T2 (N/kg)	T3 (deg/s)	T4 (N/kg)
AB01	*Early Stance*	3	0	0	3.5	0.25	0	8.5	1.84	0.3	2.18
	Late Stance	1.75	0.05	17.2	3.6	0.1	-11.5				
	Swing Flexion	1	0.05	63	2.6	0.1	1.75				
	Swing Extension	1.25	0.13	0	2.1	0.525	1.75				
AB02	*Early Stance*	3	0	0	3.5	0.25	0	5.5	1.62	0.3	1.88
	Late Stance	1.75	0.05	17.2	3.5	0.1	-10				
	Swing Flexion	1.2	0.05	63	2.6	0.1	3.5				
	Swing Extension	1.25	0.2	0	2.1	0.525	1.75				
TF01	*Early Stance*	3	0	0	3.5	0.25	0	5.15	1.06	0.3	1.47
	Late Stance	1.75	0.05	17.2	3.5	0.1	-11.5				
	Swing Flexion	1	0.05	63	2.6	0.1	1.75				
	Swing Extension	1.2	0.09	0	2.1	0.525	1.75				
TF02	*Early Stance*	3	0	0	3.5	0.25	0	8.5	1.55	0.3	1.78
	Late Stance	1.75	0.05	17.2	3.5	0.1	-11.5				
	Swing Flexion	1	0.05	63	2.6	0.1	1.75				
	Swing Extension	1.25	0.13	0	2.1	0.525	1.75				
TF03	*Early Stance*	3	0	0	3.1	0.25	0	7.0	1.60	0.3	1.87
	Late Stance	1.75	0.05	17.2	3.5	0.1	-15				
	Swing Flexion	1.1	0.05	63	2.6	0.1	5				
	Swing Extension	1.25	0.13	0	2.1	0.525	1.75				

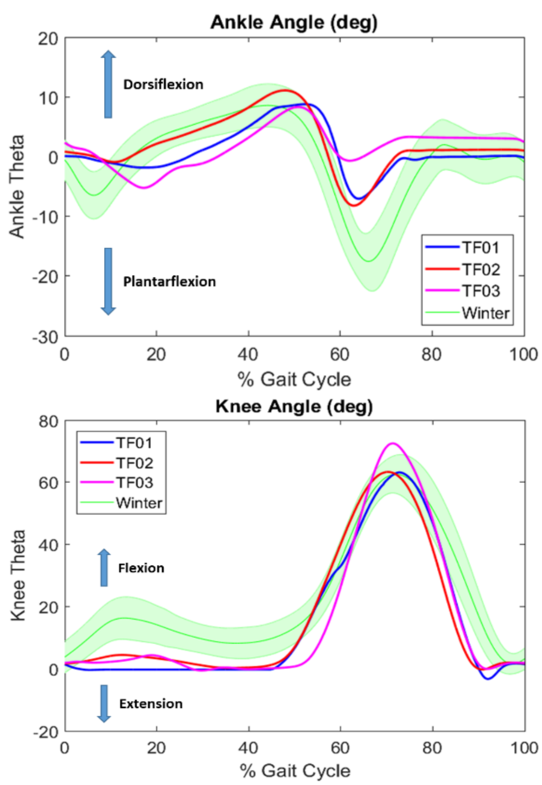


Figure 13: Kinematic data from ankle (top) and knee (bottom) joints on a prosthetic device, averaged and segmented over 40 strides plotted versus percent gait cycle compared to healthy biomechanics [24].

Two subjects with transfemoral amputation were also able to ambulate over a range of speeds from 0.63 m/s to 1.07 m/s as seen in Fig. 14. The purpose of ambulating over different speeds was to test and ensure that the device was able to accommodate and handle different conditions. For TF01, the maximum plantarflexion angles varied between -4.63 to -7.78 degrees. The maximum plantarflexion torque was 0.84 Nm/kg at 1.07 m/s. The maximum knee flexion angles varied from 63.59 to 66.92 degrees. The maximum knee torque exerted during the trials was 0.75 Nm/kg. For TF02, the maximum plantarflexion angles varied between -4.22 and -8.15. The maximum plantarflexion torque was 0.88 Nm/kg at 0.80 m/s. The maximum knee flexion angles varied from 47.36 to 64.05 degrees. The maximum knee torque exerted during the trials was 0.61 Nm/kg.

6 DISCUSSION

The prosthetic device is able to match kinematics relatively well compared to Winter's kinematic data [24]. The ankle torque is not as smooth compared to biological torque since the device is changing impedance parameters at discrete states. The knee also does not flex in early stance since users feel more comfortable walking with the device in this manner, hence there is no need to generate knee extension torque. The knee torques are greater in swing extension compared to biological values because the device must ensure that the leg is fully extended before the next heel contact. Also compared to healthy subjects, there may be reduced energy from the proximal leg to help propel the leg forward which results in the device needing to provide additional extension support. Generated torque profiles do not closely match to the Winter data, but this may be due to the fact that the device is operating under an open-loop control architecture, where the actual torque is assumed to be the desired torque.

Table 2 outlines tuning parameters across all experimental subjects. The reason that swing flexion parameters were modified was to account for providing foot clearance through the swing phase of the gait cycle. Swing extension parameters

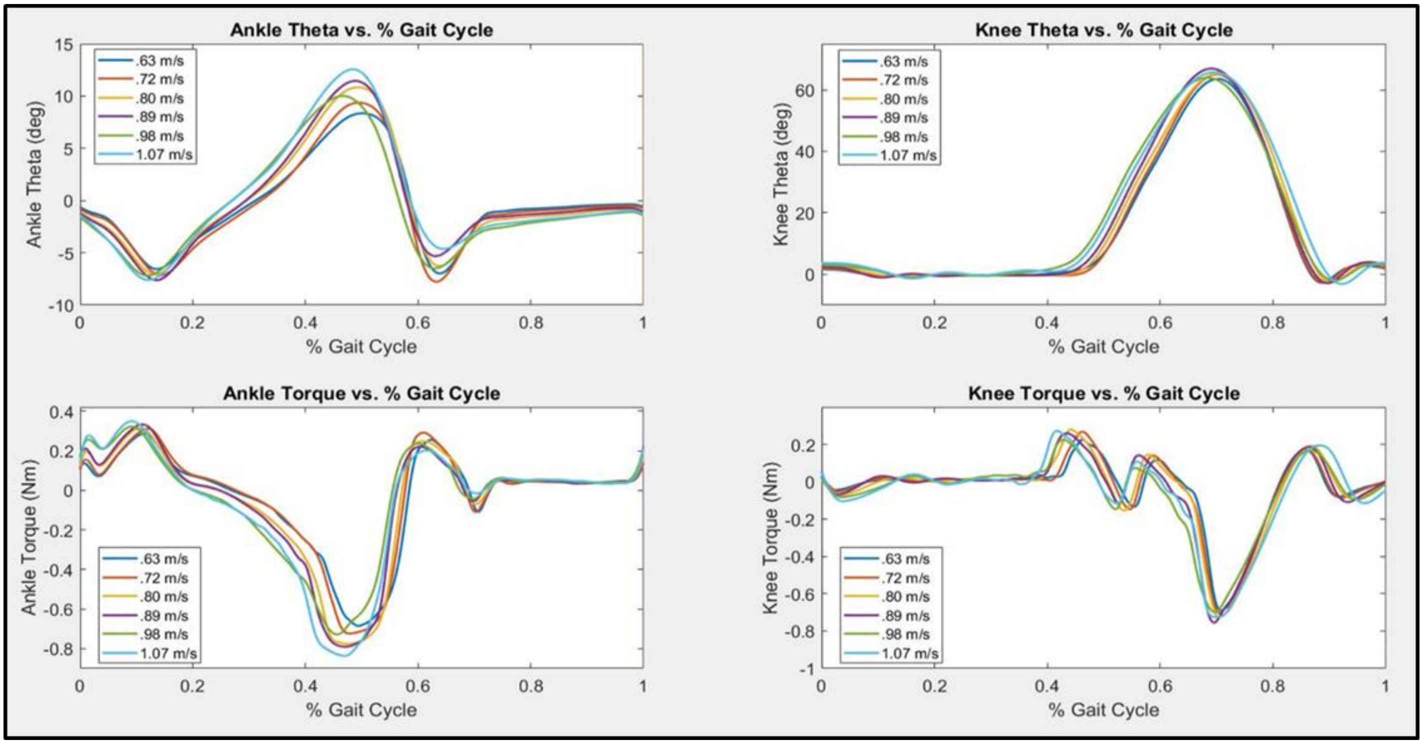


Figure 14: TF01 Kinematic and kinetics data from ankle (left) and knee (right) joints on a prosthetic device across a range of speeds.

were modified to ensure the leg was fully extended at ground contact. Changes in equilibrium angle and stiffness values in late stance for the ankle were performed to give the user better push-off mechanics. T2 and T4 were turned simultaneously based on the load cell to provide proper transitions between swing and stance phases. In particular the transition from stance to swing had to be placed earlier to render a fast transitional response of the device near toe-off. T1 was based on ankle angle and was tuned based on subject preference of when late stance assistance at the ankle was comfortable on a per subject basis. Adjusting these thresholds allowed for the user to feel more comfortable walking on the device.

One positive outcome of the device was the ease of translating the values seen in [23] into our current setup. Also we found that there was a relatively small amount of tuning needed to generate smooth walking on the device which is in contrast to common refrain in the field that impedance control is disadvantageous due to the infeasibility of tuning a large number of impedance parameters [25–27]. The implementation of our control strategies also gave the clinicians much more flexibility to adjust specific parameters of amputee gait which vary tremendously amongst patients. It is difficult to find control approaches that can provide these features that better assist the user. Another positive seen from our device is the ability to accommodate to a wide range of walking speeds without having to change the impedance parameters per speed.

One of the main challenges in the mechanical design was to allow for variable height increments for different users compared to the older design [14]. Adding a heel at the foot was useful for providing better plantar-flexor control which enabled the user to feel more comfortable with the device. The device also had an easy to change configuration that helped fit across different prosthetic socket configurations as well as the able-bodied knee adapter. Also transmitting power from the motor to the joint is a difficult problem since there are always inefficiencies which in this case are: a large gear reduction, friction effects, and mechanical hardware. Our future design iterations will try to take this into account, as well as reducing the overall weight of the device.

For preliminary testing and device validation, an open-loop control method was implemented due to restrictions of measuring the actual torque. These limitations include the poor resolution of the current absolute joint encoders attached at the output side of the device as well as large stiffness value of the torsional springs. Hence an improvement that needs to be made is to measure the actual torque. After implementing a SEA based closed loop methodology of measuring spring displacement and translating to actual torque, will allow us to determine whether the device is able to provide appropriate torques for the user. Regardless, the kinematic and kinetic data shows that this device is capable of providing enough torque needed to ambulate on level-ground walking.

In the future we would like to implement scaling equations as seen in [23] to better enhance device performance for the user and provide a better transition of torque values during different states of our mid-level control. Other future work will include configuring the device to handle multiple ambulation modes to develop a more robust controller that is able to handle different environmental conditions.

7 CONCLUSIONS

As powered prostheses become an increasingly common clinical option, the underlying factors of being easy to tune, reducing acclimation time, and providing supportive mechanical power will be important to determine success of the hardware. Device performance testing on the benchtop, with able-bodied individuals, and three individuals with transfemoral amputation validated that our device is capable of providing powered assistance to the user using a standard impedance control paradigm across a range of walking speeds. Our approach indicates that our device and overall control architecture is a good platform for further testing robust controllers that provide powered assistance to common community ambulation tasks.

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REFERENCES

[1] Ziegler-Graham, K., MacKenzie, E. J., Ephraim, P. L., Travison, T. G., and Brookmeyer, R., 2008, "Estimating the Prevalence of Limb Loss in the United States: 2005 to 2050," Arch. Phys. Med. Rehabil., **89**(3), pp. 422–429.

[2] Waters, R. L., Perry, J., Antonelli, D., and Hislop, H., 1976, "Energy Cost of Walking of Amputees: The Influence of Level of Amputation," J. Bone Joint Surg. Am., **58**(1), pp. 42–46.

[3] Young, A. J., Kuiken, T. A., and Hargrove, L. J., 2014, "Analysis of Using EMG and Mechanical Sensors to Enhance Intent Recognition in Powered Lower Limb Prostheses," J. Neural Eng., **11**(5), p. 56021.

[4] Eilenberg, M. F., Geyer, H., and Herr, H., 2010, "Control of a Powered Ankle-Foot Prosthesis Based on a Neuromuscular Model," IEEE Trans. Neural Syst. Rehabil. Eng., **18**(2), pp. 164–173.

[5] Au, S., Berniker, M., and Herr, H., 2008, "Powered Ankle-Foot Prosthesis to Assist Level-Ground and Stair-Descent Gaits," Neural Networks, **21**, pp. 654–666.

[6] OSSUR, *The POWER KNEE*, http://bionics.ossur.com/Products/POWER-KNEE/SENSE.

[7] Bellmann, M., Schmalz, T., and Blumentritt, S., 2010, "Comparative Biomechanical Analysis of Current Microprocessor-Controlled Prosthetic Knee Joints," Arch. Phys. Med. Rehabil., **91**(4), pp. 644–652.

[8] Gailey, R., 2008, "Review of Secondary Physical Conditions Associated with Lower-Limb Amputation and Long-Term Prosthesis Use," J. Rehabil. Res. Dev., **45**(1), pp. 15–30.

[9] Murray, M. P., Mollinger, L. A., Sepic, S. B., Gardner, G. M., and Linder, M. T., 1983, "Gait Patterns in Above-Knee Amputee Patients: Hydraulic Swing Control vs Constant-Friction Knee Components.," Arch. Phys. Med. Rehabil., **64**(8), pp. 339–45.

[10] Sup, F., Bohara, A., and Goldfarb, M., 2008, "Design and Control of a Powered Transfemoral Prosthesis," Int. J. Rob. Res., **27**(2), pp. 263–273.

[11] Lawson, B. E., Mitchell, J., Truex, D., Shultz, A., Ledoux, E., and Goldfarb, M., 2014, "A Robotic Leg Prosthesis: Design, Control, and Implementation," IEEE Robot. Autom. Mag., **21**(4), pp. 70–81.

[12] Liu, M., Zhang, F., Datseris, P., and Huang, H. (Helen), 2014, "Improving Finite State Impedance Control of Active-Transfemoral Prosthesis Using Dempster-Shafer Based State Transition Rules," J. Intell. Robot. Syst. Theory Appl., **76**(3–4), pp. 461–474.

[13] Hogan, N., 1985, "Impedance Control - an Approach to Manipulation .2. Implementation," J. Dyn. Syst. Meas. Control, **107**(1), pp. 8–16.

[14] Zhao, H., Ambrose, E., and Ames, A. D., 2017, "Preliminary Results on Energy Efficient 3D Prosthetic Walking with a Powered Compliant Transfemoral Prosthesis," *Proceedings - IEEE International Conference on Robotics and Automation*, pp. 1140–1147.

[15] Texas Health Surgery Center Cleburne, "What to Expect - Total Knee Replacement" [Online]. Available: http://cleburnesurgical.com/procedures-specialties/total-knee-replacement/what-to-expect/. [Accessed: 15-Apr-2018].

[16] 2010, "Planar Torsion Spring."

[17] Herr, H. M., and Grabowski, A. M., 2012, "Bionic Ankle-Foot Prosthesis Normalizes Walking Gait for Persons with Leg Amputation.," Proceedings. Biol. Sci., **279**(1728), pp. 457–64.

[18] Curtze, C., Hof, A. L., van Keeken, H. G., Halbertsma, J. P. K., Postema, K., and Otten, B., 2009, "Comparative Roll-over Analysis of Prosthetic Feet.," J. Biomech., **42**(11), pp. 1746–53.

[19] Young, A. J., Simon, A. M., Fey, N. P., and Hargrove, L. J., 2014, "Intent Recognition in a Powered Lower Limb Prosthesis Using Time History Information," Ann. Biomed. Eng., **42**(3), pp. 631–641.

[20] Young, A. J., Smith, L. H., Rouse, E. J., and Hargrove, L. J., 2014, "A Comparison of the Real-Time Controllability of Pattern Recognition to Conventional Myoelectric Control for Discrete and Simultaneous Movements," J. Neuroeng. Rehabil., **11**.

[21] Varol, H. A., Sup, F., and Goldfarb, M., 2010, "Multiclass Real-Time Intent Recognition of a Powered Lower Limb Prosthesis," IEEE Trans. Biomed. Eng., **57**(3), pp. 542–551.

[22] Spanias, J., Simon, A. M., Finucane, S., Perreault, E., and Hargrove, L., 2018, "Online Adaptive Neural Control of a Robotic Lower Limb Prosthesis," J. Neural Eng.

[23] Simon, A. M., Ingraham, K. A., Fey, N. P., Finucane, S. B., Lipschutz, R. D., Young, A. J., and Hargrove, L. J., 2014, "Configuring a Powered Knee and Ankle Prosthesis for Transfemoral Amputees within Five Specific Ambulation Modes," PLoS One, **9**(6), p. e99387.

[24] Winter, D. A., 1990, *Biomechanics and Motor Control of Human Movement*, John Wiley and Sons, Inc., New York.

[25] Wen, Y., Si, J., Gao, X., Huang, S., Huang, H. H., and Member, S., 2016, "A New Powered Lower Limb Prosthesis Control Framework Based on Adaptive Dynamic Programming," IEEE Trans. Neural Networks Learn. Syst., pp. 1–6.

[26] Huang, H., Crouch, D. L., Liu, M., Sawicki, G. S., and Wang, D., 2016, "A Cyber Expert System for Auto-Tuning Powered Prosthesis Impedance Control Parameters," Ann. Biomed. Eng., **44**(5), pp. 1613–1624.

[27] Gregg, R. D., Lenzi, T., Hargrove, L. J., and Sensinger, J. W., 2014, "Virtual Constraint Control of a Powered Prosthetic Leg: From Simulation to Experiments with Transfemoral Amputees," IEEE Trans Robot, **30**(6), pp. 1455–1471.

Appendix C: ASME DSCC Conference Paper #2
Title: Stochastic Optimization of Impedance Parameters for a Powered Prosthesis Using a 3D Simulation Environment
Authors: Jonathan Camargo, Krishan Bhakta, Aaron J Young
Date of Conference: September 30th – October 3rd 2018
Session Title: Modeling and Simulation
Location of Conference: Atlanta, Georgia

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September 30-October 3, 2018, Atlanta, Georgia, USA

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STOCHASTIC OPTIMIZATION OF IMPEDANCE PARAMETERS FOR A POWERED PROSTHESIS USING A 3D SIMULATION ENVIRONMENT

Jonathan Camargo
Department of Mechanical Engineering
Georgia Institute of Technology
Atlanta, GA, USA
jon-cama@gatech.edu

Krishan Bhakta
Department of Mechanical Engineering
Georgia Institute of Technology
Atlanta, GA, USA
kbhakta3@gatech.edu

Aaron Young
Department of Mechanical Engineering
Georgia Institute of Technology
Atlanta, GA, USA
aaron.young@me.gatech.edu

ABSTRACT

Developing controllers for powered prostheses is a daunting task that requires involvement from clinicians, patients and robotics experts. Difficulties arise for tuning prosthetic devices that perform in multiple conditions and provide more functionality to the user. For this reason, we propose the implementation of a simulation framework based on the open-source 3D simulation environment Gazebo, to reduce the burden of experimentation and aid in the early stages of development. In this study, we present a minimalist plugin for the simulator that allows the interfacing of a virtual model with the native prosthesis controller and renders the finding of impedance parameters as a pattern search problem. To demonstrate the functionality of this approach, we used the framework to obtain the parameters that offer the most similar joint trajectory to the respective biological counterpart during swing phase for ground level walking. The optimization results are compared against the response of a physical 2DOF knee-ankle prosthesis operating under the optimized parameters, showing congruence to our model-based results. We found that a simulation-based solution is capable of finding parameters that create an emerging behavior that approximates to the kinematic trajectory goals within a tolerance (mean absolute error ~10%). This provides an appropriate method for development and evaluation of impedance-based controllers before deployment to the physical device.

INTRODUCTION

Taking inspiration from the motor patterns in humans, biomimicry has helped advance the field of prosthetics. Ivanenko et al. studied the spatiotemporal maps of motor neuron activation during locomotion, finding that human motor control during walking shows discrete periods of activity [1]. By recording EMG signals during walking on a treadmill at different speeds, researchers obtained a transient map of motor neuron activity. From this, they suggested that the activity of locomotion could be represented by five periods of motor neuron activation.

Discrete states prostheses use a similar approach for generation of locomotion patterns. A common method for state of the art devices is the use of impedance-based control with parameters that dynamically activate on these discrete events [2]–[4]. Impedance control defines the interaction of an input of position (or velocity) and the resulting force (or torque) on a system [5]. Thus, when defining this interaction, the controller must specify dynamic parameters of behavior such as stiffness, damping and equilibrium position. The compliance of an impedance-based controller offers the advantage of good adaptability and human-device interaction, which provides better response than pure motion control [6]. However, this method has the drawback of a potentially steep difficulty in determining the configuration of parameters that are required under each task. For powered prostheses, it usually requires an expert with practice on how the parameters affect the behavior. In addition, it needs a person wearing the device, and be subject to time-consuming experimentation.

The problem increases when developing multiple ambulation modes and terrain conditions, since it requires the assignment of values for parameter sets that produce different kinematics and kinetics responses for each terrain or mode evaluated. Some authors have proposed techniques to reduce the burden of clinical experiments by generating empirical tuning rules and equations. For example, Simon et al. presented a powered knee ankle prosthesis that offers five ambulation modes together with intrinsic control strategies and a set of starting configuration parameters. This method provides joint impedance parameters that scale according to the kinematics signals, user's characteristics and some empirical constants found experimentally [7].

Other works have tried to use AI and optimization methods to aid with the configuration process. They completely rely on the use of a physical prosthesis, together with experimental protocols and human experts that provide empirical tuning rules. Huang et al. encoded a set of human expert tuning rules in a fuzzy logic tuner that applied the rules online during able body walking on a treadmill. This cyber-expert approach relies on the previous information given from a human expert and still requires an initial manual configuration [8]. Abdelhady et al. suggests the use of optimization algorithms for tuning the controller of the knee joint during the swing motion. The authors present a process for finding PID controller parameters using an optimization with hardware in the loop. This allows adjusting the motion for the swing phase without the need of experiments with patients, providing a suitable alternative for reducing the needs of testing with the final user [9].

With this context, it is evident that the field needs to develop better tools for configuration of walking controllers, to reduce the need of experimentation and provide a safe testing framework for developers. For this reason, we propose the use of simulation to estimate an initial set of parameters based on a model of a knee-ankle prosthesis driven by the same logic that drives the physical device. This would provide the benefit of reducing the encumbrance of experimental configuration of the parameters, and offer a platform for developing, debugging and testing different controllers.

Some authors have developed computer simulations of bipedal locomotion before as a constrained mechanical system to estimate the kinematic response of controllers[10] and drive the design phase of a prosthesis by studying the energy expenditure[11]. These solutions allow the simulation of walking only under a constrained situation and require the controller to be translated to a set of DAE (differential algebraic equations). In contrast, we implement a framework that enables the simulation of our prosthetic device, by driving a virtual model using the same controlling firmware as the one used by the real device. The framework captures the response of the virtual device under different parameters of operation, providing a reference model to evaluate the performance of the system, and allowing its use for validation of different controller's logic. Furthermore, we propose the use of the framework to realize an optimization process that, through a minimization of a trajectory cost function, finds the best set of parameters that drive the device during a representative task, in this case, the swing phase of ground level walking.

METHODS

Power prosthesis operation

We based the controller on the concept of impedance control, as outlined by previous researchers using powered knee-ankle prostheses [3], [4], [12]. This has advantages of providing better adaptation to different terrains and changes in user ambulation in clinical trials compared with other approaches in the field to date. The logic of the controller is to divide the locomotion into phases that require a specific type of interaction between the forces produced by the system and its current kinematic state. Such interaction is regulated by changing virtual dynamic parameters: joint stiffness, damping and equilibrium position. With this approach, the definition of a task like ground level walking translates to the constitution of a finite state machine (Figure 1) that transitions through the phases, and the parameters associated to each phase. These parameters provide the control law for the impedance equation (Eq. 1).

$$\tau = -k\left(\theta - \theta_{eq}\right) - b\dot{\theta} \quad (1)$$

In this equation, joint torque (τ) is proportional to the difference of the joint angle (θ) and the equilibrium angle (θ_{eq}); providing an actuator excitation with the intention to reach a desired position, but offering a compliant result that is regulated by the selection of a stiffness value (k) representing how rigid is the joint, and a damping term (b) that acts as a virtual viscous friction.

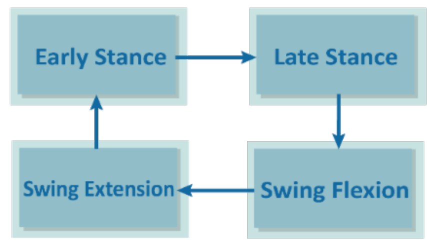

Figure 1. Finite state machine for ground level walking. Gait cycle is divided in a four states machine that modifies the controller parameters during operation.

For the finite state machine like the one presented in Figure 1, the response of the device is thus defined by the values k, b, and θ_{eq}, for each one of the four states and both active joints in the prosthesis. This derives in a problem of setting up 24 different parameters before the device can operate to enable ground level walking.

Overview of the optimization process

A virtual model allows the verification of the controllers by means of a simulated environment, reducing the dependency of experimental evaluation and easing the debugging process during software development. Additionally, we are interested in benefit from the functionality of the framework by using it to tune the parameters using a stochastic optimization process that searches for the best set of parameters for a given motion task, represented by a control algorithm.

Figure 2. presents the block diagram of the complete process of stochastic optimization of the controller parameters. In the previous section, we discussed the control law used for the joints and defined the parameters that are associated to its operation. As seen in the block diagram, the model connects directly to the controller, offering the closest resemblance to the operation with the device. Thus, the model block, describes the behavior of the device and represents the simulation of the power prosthesis. The analysis block transforms the simulation results in a scalar cost function used to evaluate the performance metrics, and the optimization block iterates to adjust the parameters accordingly. In the following sections, the methods involved in the implementation of these blocks are described.

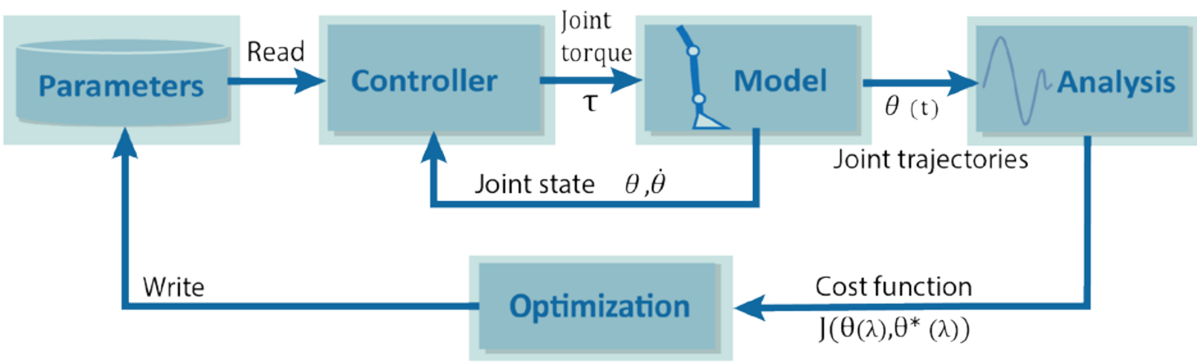

Figure 2. Overview of the optimization process: the controller module executes the power prosthesis controller firmware based on ROS. Model is the virtual representation of the device in the Gazebo environment. Simulation results are analyzed using a biological trajectory reference, creating an optimization cost function that is used in a pattern search optimization that sets the parameters for the device operation.

Model

With the results from the multibody dynamics survey from Ivaldi [13], and after some exploration with different software packages, we opted for using Gazebo simulator [14] as the core of the framework. This gave us the benefits of open source and better compatibility with our controllers, that operate using Robot Operating System *(ROS)* [15]. The device of study is a powered prosthesis with two active DOF electrically actuated, one passive DOF, as presented in Figure 4 . It is an updated design based on AMPRO3 [16] from a collaboration between Exoskeleton and Prosthesis Intelligent Control (EPIC) at Georgia Institute of Technology, with the Advanced Mechanical Bipedal Experimental Robotics Lab (AMBER) at California Institute of Technology. The model of the device was produced in the SDF format [17] based on information obtained from both the CAD model (robot kinematics, visual geometry, inertia tensor estimation) and the physical device (mass, damping estimation).

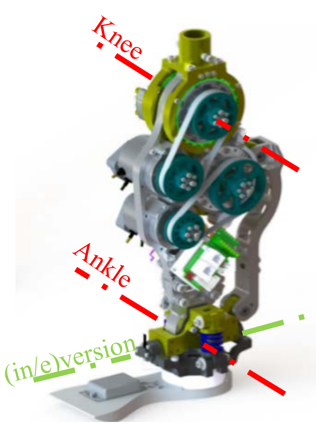

Figure 3. Powered prosthesis. A knee and ankle prosthesis with active ankle plantarflexion/dorsiflexion, knee flexion/extension, and passive inversion/eversion. The sensors include: joint encoders, IMU for each link and a 6DOF loadcell incorporated in the foot.

Mass was measured by a scale using the machined parts of the device, and damping was estimated using a linearized model of the system response to a set of step torque inputs covering the range of operation (0 – 20 Nm). Finding damping values of 5.60 Nms for the knee and 2.47 Nms for the ankle, and standard deviation of 1.33 Nms and 0.7 Nms respectively. Step responses for each joint are shown in Figure 4.

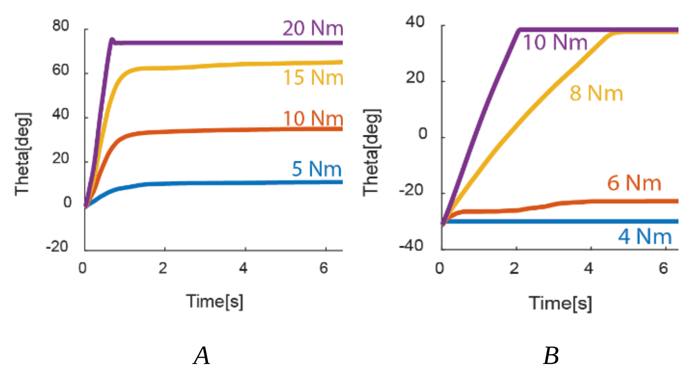

Figure 4. Experimental step response on the physical device. Figure shows the average of 10 trials of the step response each different torque input. A. Knee joint. B. Ankle joint.

We developed a custom plugin for gazebo to interface the model to the ROS environment by two signals: joint state $(\theta, \dot{\theta})$ and torque (τ). These signals use the same format than the real device. Therefore, we do not require any modifications to our controller firmware. This allowed the interface with the model through ROS ecosystem, exposing the signals from the joint state in the simulation and creating a way to send torque actions to the joints. This effectively allows commanding the joints with a particular torque (revolute joint) or force (prismatic joint) and permits the recording of the joint position and velocity information. The inheritance diagram of the plugin is presented in Figure 5. Where the class EffortPlugin handles the interaction with the API of the Gazebo environment and RosEffort creates the interface with ROS. Once the simulations are launched, the plugin is loaded to the model and torque commands can be calculated by the external controller that receives the model state. This represents the core of the framework, constituting a fully connectable virtual model of the prosthesis.

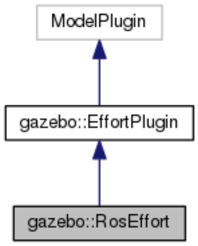

Figure 5. Class Inheritance for the Gazebo-ROS effort plugin. RosEffort class exposes the joint state with an ROS publisher and the torque with an ROS subscriber

The plugin can be instantiated from the SDF file, where the user can select specific joints to be exposed to ROS. For this study, we solely configured interaction to the knee and ankle joints, leaving the inversion/eversion joint rigid and not recorded. Using the Gazebo environment and running the controller on the same ROS network, we created a simulation solution that opens different possibilities for controller development.

Analysis

After the simulation, the results from the virtual device motion can be postprocessed to produce a scalar value that represents how well the response fits the desired behavior. Such behavior could be interpreted in the sense of energy expenditure, kinematics, kinetics, or stability. As our initial outcome is to mimic biological trajectory we propose the cost function given by Eq. 2, with θ_i^* corresponding to the desired trajectory.

$$J_i = \frac{\|\theta_i(\lambda) - \theta_i{}^*(\lambda)\|}{\|\theta_i(\lambda)^*\|} \quad (2)$$

The cost function uses the L-2 norm of the difference of the simulated trajectory with respect to the desired trajectory in the interval of the non-dimensional time of the state in the swing phase ($\lambda \in \Re | 0 \leq \lambda \leq 1$). This is normalized to the squared root of the energy of the goal function $\theta_i^*(\lambda)$ to allow for the comparison of the error signal to the desired signal. The scalar cost function of the optimization process is then the Euclidean norm of each joint cost. For natural ground level walking, goal trajectories are selected to be the biological profile of the knee and ankle as reported by Winter [18].

Optimization

For the optimization process we chose a pattern search algorithm [19], this method offers an efficient alternative to do a broad search of the cost function on the parameter space. The process consists of launching simulations at each iteration (k), over points of a variable size mesh (M_k) given by eq 3. This mesh is constructed around center point (x_k) and following the directions D. Directions, are chosen with the mesh adaptive direct search (MADS) algorithm [20], [21] that makes the mesh narrow down to the direction of the best result obtained.

$$M_k = x_k + \{\Delta_k d_j \mid d_j \in D\} \quad (3)$$

RESULTS

To evaluate the functionality, we run the optimization to find 8 parameters comprising equilibrium angles and stiffness for swing flexion and extension. The parameter domain intervals are reported in Table 1. Damping term was not included in the optimization process. Since the system identification showed a high damping factor for the prosthesis joints and from preliminary exploration of the simulations, we observed that the response is not sensitive to small changes in the damping parameter. This makes the joints of the real device a highly damped system and thus we considered only the stiffness and equilibrium terms in the optimization process.

Table 1. Domain for parameter search

	Swing Flexion		*Swing Extension*	
	Knee	*Ankle*	*Knee*	*Ankle*
k[Nm/deg]	0 to 8	0 to 8	0 to 8	0 to 8
θ_{eq}[deg]	30 to 80	-20 to 20	-10 to 20	-20 to 20

Exploring this search domain, we found multiple sets of parameters and the associated performance given by the cost function. Figure 6. details the simulation results, where each line shows a specific combination of parameters that was executed in simulation. The color scale represents the resulting value of the cost function.

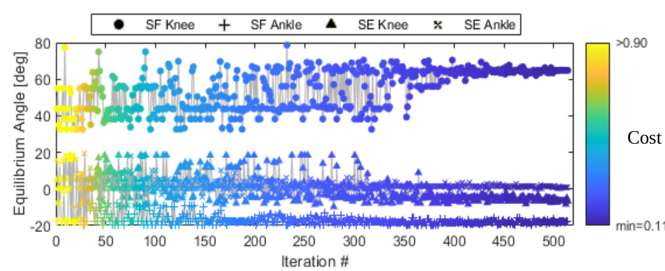

Figure 6. Equilibrium angle parameters explored during optimization

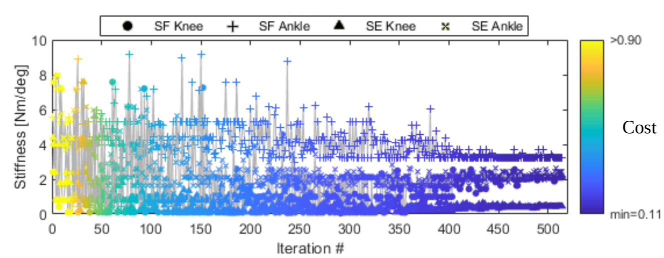

Figure 7. Stiffness parameters explored during optimization.

The best set of parameters were found after ~500 searching iterations, the corresponding values are presented in Table 2.

Table 2. Domain for parameter search

	Swing Flexion		*Swing Extension*	
	Knee	*Ankle*	*Knee*	*Ankle*
k (Nm/deg)	2.11	3.23	0.64	2.41
θ_{eq} (deg)	64.9	-17.93	-3.67	0.63

Signals from the simulation can be recorded using regular ROS tools (e.g. rosbag) and thus, we collected the simulation profiles to visually compare against the desired trajectory. Figure 8 presents the best 10% of the simulated trajectories as a shaded profile compared to the goal trajectory. Profiles are plotted with respect to the non-dimensional time λ that represents the lapse of swing phase. For the ankle joint, we found a mean error of 3.9% (0.77°) of the goal angle range, and for the knee, a mean error of 6.2% (4.01°) of the goal angle range. Ankle plantar flexion achieved a peak value of -18.4° and knee flexion reached a peak value of 62.5°. This shows that the simulation can effectively recreate trajectories close to the biological motion.

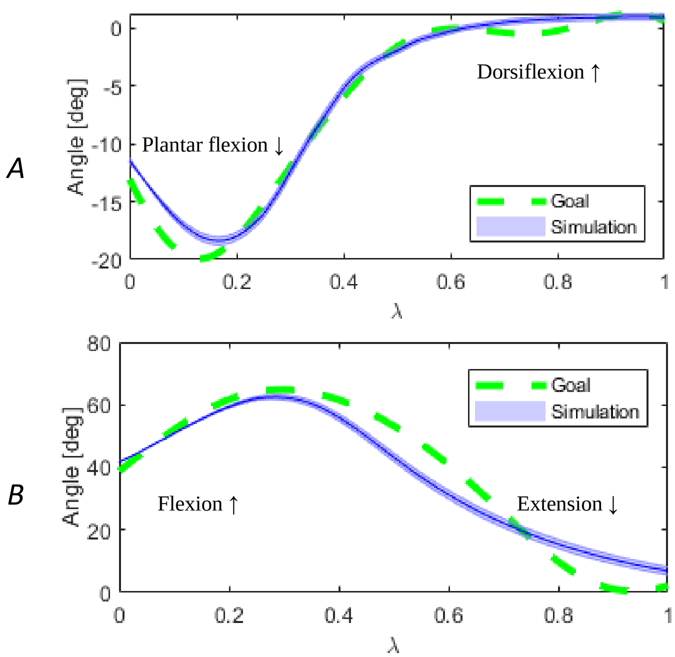

Figure 8. Optimization results. Average and standard deviation of the trajectory of the best 10% of the optimization results compared to the desired response. A. Ankle trajectory B. Knee trajectory.

As a final validation of the simulation results, we run the physical device under the swing parameters obtained from simulation. Joint trajectories were recorded from able body level walking ambulation on a treadmill at a speed of 0.58m/s. The average and standard deviation of n=32 swing profiles are shown in Figure 9, contrasted to the best simulated profile. With respect to the experimental validation, for the ankle joint, we found a mean difference of 13.6% (2.62°) of the goal angle range, and for the knee, a mean error of 12.53% (8.02°) angle range. Ankle plantar flexion shows a mean peak at -18.77° and knee flexion reached 61.2° during swing. The mean and standard deviation of trajectory profile obtained in the validation are presented in Figure 9. For comparison, the best simulated profile and the goal trajectory are also displayed.

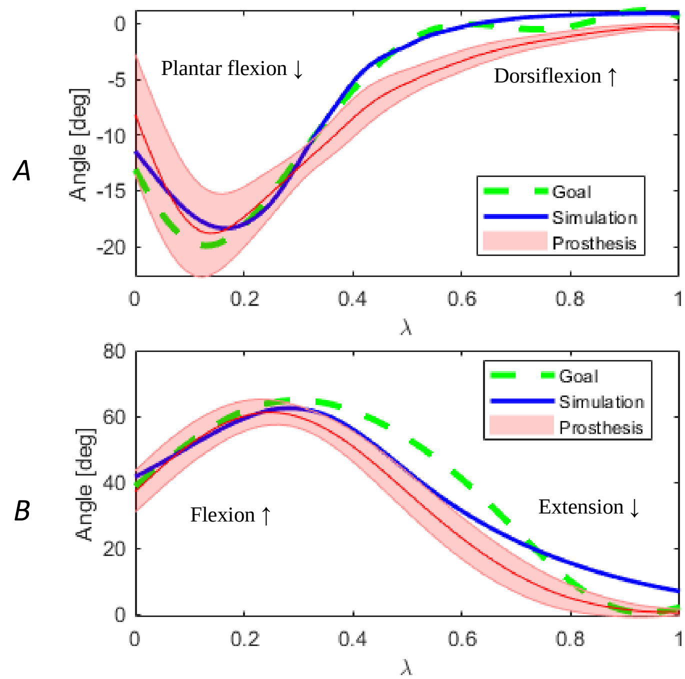

Figure 9. Validation by implementing parameters on the physical device. A. Ankle trajectory B. Knee trajectory.

DISCUSSION

We utilized the simulation framework to develop an optimization-based search for eight impedance parameters, consisting of stiffness and equilibrium angle for knee and ankle joints during swing flexion and swing extension phases of ground level walking. The process required running 514 simulations under different parameter combinations before converging within the minimum 5% of the cost function. With an average running time of 1.2s per simulation, the approach seems feasible for using in more complex situations, where parallelization could be exploited to reduce wall time.

The optimal set of parameters found in the process was consistent with experimental results with the real powered prosthesis, following an overall trajectory similar to the biological profile goal. The response showed some differences with respect the experimental validation results, were the path did not accurately match the simulated trajectory. As we found in the system identification process (Figure 4), non-linear characteristics are present in the damping; this can potentially introduce a difference that was not accounted in the model, which uses a linear damping term.

From the simulation results, it is evident that the controller is not able to perfectly track the biological trajectory. This expected limitation is due to the discrete operation that switches between different sets of parameters. In comparison to a pure trajectory tracking control, this approach allows more flexibility in the response of the device to external perturbations and interaction forces. This translates to a tradeoff between compliance (seen as the variable stiffness of the joints) versus reaching an accurate trajectory. Nevertheless, for aesthetic purposes and patient's acceptance, we want to provide the users with a response close to the biological, and in the case of swing motion; this was the most important target to achieve. Other optimization goals could provide a reduction in energy expenditure, terrain adaptability, robustness to perturbation, etc. These were beyond the scope of this initial study. Other authors have proposed the use of non-linear controllers that incorporate impedance control law as a feedforward term or virtual constraints, to increase the performance of prostheses in terms of tracking accuracy or energy efficiency [16], [22]. These alternatives could also serve as way of simplifying the parameters tuning process, where a virtual framework would provide an intuitive tool for developers and clinicians.

CONCLUSION

We developed a framework for optimization of impedance parameters for the Gazebo simulator software. Using a virtual model of a powered knee-ankle prosthesis, we implemented the optimization of impedance parameters during swing phase. This approach could provide adequate usability and advantage for virtual verification and debugging in the early stages of controller development. Additionally, it can serve as a tool for parameter tuning, allowing the execution of this process in using a realistic physics engine to estimate device response without doing physical experimentation. This is advantageous because it reduces in-person tuning of prosthesis parameters and saves signficant efforts and time in implementing impedance based controllers for prostheses. The plugin for Gazebo is publicly released under an opensource repository with MIT License [23]. This type of virtual model opens various possibilities for simulation of simple and controlled conditions, but it is still limited for its use in the full human-device interaction, lacking inputs equivalent to the person that is using the device. Future work should aim towards the development of ground contact information and hip motion to simulate a more comprehensive walking activity.

ACKNOWLEDGMENT

This work was supported by the Office of the Assistant Secretary of Defense for Health Affairs through the Orthotics and Prosthetics Outcomes Research Program Prosthetics Outcomes Research Award under Award No. W81XWH-17-1-0031. Authors thank Dr. Gregory Sawicki for his helpful advice, Aditya Ramanathan, Noel Csomay-Shanklin and Kevin Dai for the assistance during data collection for system identification. J.C. acknowledges support from the Fulbright Foreign Scholarship and Colciencias.

REFERENCES

[1] Y. P. Ivanenko, R. E. Poppele, and F. Lacquaniti, "Motor control programs and walking," *Neuroscientist*, vol. 12, no. 4, pp. 339–348, 2006.

[2] B. E. Lawson, J. Mitchell, D. Truex, A. Shultz, E. Ledoux, and M. Goldfarb, "A robotic leg prosthesis: Design, control, and implementation," *IEEE Robot. Autom. Mag.*, vol. 21, no. 4, pp. 70–81, 2014.

[3] F. Sup, A. Bohara, and M. Goldfarb, "Design and control of a powered transfemoral prosthesis," *Int. J. Rob. Res.*, vol. 27, no. 2, pp. 263–273, 2008.

[4] M. Liu, F. Zhang, P. Datseris, and H. (Helen) Huang, "Improving Finite State Impedance Control of Active-Transfemoral Prosthesis Using Dempster-Shafer Based State Transition Rules," *J. Intell. Robot. Syst. Theory Appl.*, vol. 76, no. 3–4, pp. 461–474, 2014.

[5] N. Hogan, "Impedance Control: An Approach to Manipulation," *Am. Control Conf. 1984 IS - SN - VO -*, no. March, pp. 304–313, 1985.

[6] H. Mohammadi and H. Richter, "Robust tracking/impedance control: Application to prosthetics," *Proc. Am. Control Conf.*, vol. 2015–July, pp. 2673–2678, 2015.

[7] A. M. Simon *et al.*, "Configuring a powered knee and ankle prosthesis for transfemoral amputees within five specific ambulation modes," *PLoS One*, vol. 9, no. 6, 2014.

[8] H. Huang, D. L. Crouch, M. Liu, G. S. Sawicki, and D. Wang, "A Cyber Expert System for Auto-Tuning Powered Prosthesis Impedance Control Parameters," *Ann. Biomed. Eng.*, vol. 44, no. 5, pp. 1613–1624, 2016.

[9] M. Abdelhady, A. Rashvand, H. Richter, and D. Simon, "System Identification and Control Optimization for an Active Prosthetic Knee in Swing Phase," *Embeddedlab.Csuohio.Edu*, 2017.

[10] D. J. Braun and M. Goldfarb, "Simulation of Constrained Mechanical Systems—Part II: Explicit Numerical Integration," *J. Appl. Mech.*, vol. 79, no. 4, p. 41018, 2012.

[11] M. L. Handford and M. Srinivasan, "Robotic lower limb prosthesis design through simultaneous computer optimizations of human and prosthesis costs," *Sci. Rep.*, vol. 6, no. September 2015, pp. 1–7, 2016.

[12] L. J. Hargrove *et al.*, "Intuitive control of a powered prosthetic leg during ambulation: a randomized clinical trial.," *Jama*, vol. 313, no. 22, pp. 2244–52, 2015.

[13] S. Ivaldi, V. Padois, and F. Nori, "Tools for dynamics simulation of robots: a survey based on user feedback," pp. 1–15, 2014.

[14] "Gazebo, Robot simulation." [Online]. Available: www.gazebosim.org.

[15] "ROS." [Online]. Available: http://www.ros.org/.

[16] H. Zhao, E. Ambrose, and A. D. Ames, "Preliminary results on energy efficient 3D prosthetic walking with a powered compliant transfemoral prosthesis," *Proc. - IEEE Int. Conf. Robot. Autom.*, pp. 1140–1147, 2017.

[17] "SDF." [Online]. Available: http://sdformat.org/.

[18] D. A. Winter, *The Biomechanics and motor control of human gait*. John Wiley & Sons, 2009.

[19] N. V. Findler, C. Lo, and R. Lo, "Pattern search for optimization," *Math. Comput. Simul.*, vol. 29, no. 1, pp. 41–50, 1987.

[20] C. Audet and J. E. Dennis, "Analysis of Generalized Pattern Searches," *SIAM J. Optim.*, vol. 13, no. 3, pp. 889–903, 2002.

[21] M. A. Abramson, C. Audet, J. E. Dennis, and S. Le Digabel, "OrthoMADS: A Deterministic MADS Instance with Orthogonal Directions," *SIAM J. Optim.*, vol. 20, no. 2, pp. 948–966, 2009.

[22] S. Kumar, A. Mohammadi, N. Gans, and R. D. Gregg, "Automatic Tuning of Virtual Constraint-Based Control Algorithms for Powered Knee-Ankle Prostheses," *IEEE Conf. Control Technol. Appl.*, 2017.

[23] "RosGazeboEffortPlugin." [Online]. Available: https://github.com/JonathanCamargo/RosGazeboEffortPlugin.git.

Appendix D: IEEE EMBC 2018

Title: Continuous Walking Speed Estimation using Neural Networks and Multi-Sensor Data Fusion

Authors: Jonathan Camargo, Noel Csomay-Shanklin, Bharat Kanwar, Aaron Young

Date of Conference: July 17th – July 21st 2018

Location of Conference: Honolulu, Hawaii

Continuous Walking Speed Estimation using Neural Networks and Multi-Sensor Data Fusion

Jonathan Camargo, Noel Csomay-Shanklin, Bharat Kanwar and Aaron Young. Member, IEEE

***Abstract*— Walking speed is a relevant parameter for diagnosing health conditions and assessing fall risk. We propose a novel approach that uses multi-sensor data fusion techniques from sensors attached to the human body to predict walking speed as a continuous variable, without requiring a kinematic model of human walking. For the walking speed range of 0.6 m/s to 1.6 m/s, our method predicts walking speeds it has not been trained on with a mean squared error of 4.5%, only a 0.60% increase compared to a network trained on all speeds. With this approach, we can achieve higher resolution in speed estimation than traditional discrete classification methods.**

Keywords - Sensor Fusion, Walking Speed Prediction, Machine Learning, Neural Networks

I. Introduction

Changes in walking speed represents a quantitative measurement for predicting different health conditions and is a main component in fall risk assessment [1, 2]. In clinical applications, gait parameters are often estimated by observation and timing or by using external sensors such as motion capture systems [3]. To reduce the complexity of measurement systems, and enable monitoring outside of the lab, researchers explore the development of methods for estimation of gait parameters based on wearable sensors. Most prominent examples use Kalman filters to make an optimal estimation. These methods estimate speed as a continuous variable but require a reduced order model of the kinematics [4]. Machine learning methods are not constrained by the definition of a prior kinematics model, but usually handle the speed as a categorical variable (e.g low, medium, high).

Using sensor fusion, we propose the use of a neural network(NN) as a continuous regression model to predict the walking speed at 20Hz based on the information extracted from the last 250ms window of data.

II. Methods

A flat ground treadmill walking experiment was conducted on three able-bodied subjects (age(yr): 21,19,22; weight(kg): 88.5,56.7,61.2; height(m): 1.75,1.65,1.70) after giving informed consent to an IRB approved protocol. Subjects were instrumented on one leg with EMG on major lower limb muscles, 3 IMU (one per segment), 3 electrogoniometers (one per joint), and FSR heel contact sensors to parse the gait cycle during post-processing. Subjects walked on a treadmill for 30 seconds at speeds in a range from 0.4 to 1.8 m/s.

We extracted time domain features from each moving window of data, and reduced the dimensionality by selecting the top ten features according to heuristic criteria from feature visualization. NN architecture is single hidden layer with size 8. In order to assume continuity of the overall network speed predictions, multiple networks were trained, each with one of the speeds removed from the training data. Each network was then tested on the speed removed from its training set and the mean-squared speed prediction errors were recorded. With sufficiently small errors, the assumption of continuity holds.

III. Results and Discussion

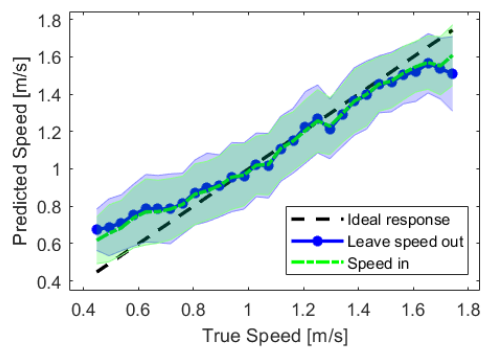

Figure 2. Speed prediction results on test data of a NN. “Speed in” was trained with samples of all the speeds; “Leave speed out” was trained with samples from all speeds except the testing speed. Shaded area is ±SD.

When randomly selecting training and testing data among discrete walking speeds between 0.6 and 1.6 m/s and comparing the prediction of the NN to the true value, a mean squared error of 3.90% of true speed value was achieved. By reserving individual walking speeds as part of a test set, and training the algorithm on the remaining walking speeds from the experiment, the NN was able to predict walking speeds with a mean squared error of 4.50%. This marginal increase in error demonstrates that the resulting NN is able to interpolate unknown speeds based on other sampled speeds, and can estimate walking speed continuously with a high degree of accuracy and not only at the discrete points in which it was trained.

References

[1] N. M. Peel, S. S. Kuys, K. Klein. *Gait Speed as a Measure in Geriatric Assessment in Clinical Settings: A Systematic Review.* J Gerontol A Biol Sci Med Sci. 2012 January;68(1):3946

[2] S. Studenski, S. Perera; K. Patel, et al *Gait Speed and Survival in Older Adults.* JAMA. 2011;305(1):50-58.

[3] D. Quintero, D. J. Lambert, D. J. Villarreal, and R. D. Gregg. *Real-Time Continuous Gait Phase and Speed Estimation from a Single Sensor.* CCTA. 2017;847-852.

[4] T. Bennett , R. Jafari, and N. Gans. *An Extended Kalman Filter to Estimate Human Gait Parameters and Walking Distance.* ACC. 2013;752-757.

Appendix E: 45th Meeting of the American Academy of Orthotists & Prosthetists

Title: Effect of Experimental Powered Prosthesis on Hip Kinetics: A single Case Pilot Study

Authors: Krishan Bhakta, Jonathan Camargo Leyva, Maximillian Spencer, Brian White, Noah Cho, Kinsey Herrin, Lee Childers, Aaron Young

Date of Conference: March 6th - 9th 2019

Location of Conference: Orlando, Florida

EFFECT OF EXPERIMENTAL POWERED PROSTHESIS ON HIP KINETICS: A SINGLE CASE PILOT STUDY

Bhakta K[1], Camargo J[1], Spencer MT[2], White BJ[2], Cho N[1], Herrin KR[2], Childers WL[3,4,5], Young AJ[1]
[1]School of Mechanical Engineering, College of Engineering, Georgia Institute of Technology, Atlanta, GA USA
[2]School of Biological Sciences, College of Sciences, Georgia Institute of Technology, Atlanta, GA USA
[3]Center for the Intrepid, Department of Rehabilitation Medicine, Brooke Army Medical Center, JBSA Ft. Sam Houston, TX, USA
[4]DoD/VA Extremity Trauma and Amputation Center of Excellence, JBSA Ft. Sam Houston, TX, USA
[5]Department of Physical Medicine and Rehabilitation, Uniformed Services University of the Health Sciences, Bethesda, MD, USA

INTRODUCTION

Individuals with transfemoral amputation (TFA) exert up to three times more hip power on their prosthetic side (Winter 1991). Hip hiking and other gait deviations compensate for power lost from absent biological muscles. However, an experimental powered knee-ankle prosthesis (Graham et al., 2016) has been shown to replace the missing biological forces generated by muscles and is especially useful during ambulation over slopes. The purpose of this case study was to compare the biomechanical effects of the powered knee-ankle prosthesis to the subject's passive microprocessor system.

METHOD

Subject: One 37 y/o male (183cm, 98.5kg, K4) with a right TFA consented to participate in this IRB approved case study.

Apparatus: Motion capture system (Vicon, Centennial, CO) and split-belt instrumented treadmill (Bertec, Columbus, OH).

Procedures: Retroreflective markers were placed on the subject, the habitual passive microprocessor prosthesis (Otto Bock C-Leg, Triton VS Foot), and the powered prosthesis (Fig. 1). Data was collected during up slope walking and down slope (7.5º and 1.0 m/s) and level ground walking trials (1.0 m/s, and 1.2 m/s) for each prosthesis. Joint moments were compared between the passive and powered knee-ankle systems without statistical analysis to highlight potential areas future larger studies may focus on.

RESULTS

Over level ground, the powered prosthesis reduced hip flexion moment during pre-swing compared to the passive prosthesis (*Fig. 2*). This same reduction in hip flexor moment was observed both for ramp ascent and ramp descent circuits (*Fig. 3*). In contrast, while using the powered prosthesis, hip extensor moments on the sound side increased compared to use with the passive prosthesis (not shown).

DISCUSSION

The reduction of hip flexor moment seen with the powered prosthesis during terminal stance/initial swing is particularly relevant for subjects with TFA as this motion is critical for advancement of the prosthetic side. With the powered prosthesis, the assistance shown during walking could potentially reduce risk of hip and back related secondary musculoskeletal pathologies, which are common clinical problems in this population. The increase in hip extension moment on the sound side is likely due to the increased weight (+4.5kg) of the experimental prosthesis and the need to stabilize the core to properly plant the device during initial contact. While this study is limited by the n=1 design, we anticipate similar results as other subjects participate in this study.

CLINICAL APPLICATIONS

The development of powered prostheses is an important area for research as these devices can restore lost biomechanical function to the user and potentially improve their quality of life over time. When these devices are shown to have improved efficacy over current clinical standards, then they are more likely to be reimbursed by third party payers and implemented into modern clinical practice.

REFERENCES

Winter DA. *Biomechanics and motor control of human gait: normal, elderly and pathological.* 1991
Graham KA,et al. *PLoS One.* 2016;11(1):e0147661.

AKNOWLEDGEMENTS

This work was funded by DOD Award No. W81XWH-17-1-0031.The view(s) expressed herein are those of the author(s) and do not reflect the official policy or position of Brooke Army Medical Center, the U.S. Army Medical Department, the U.S. Army Office of the Surgeon General, the Department of the Air Force, the Department of the Army or the Department of Defense or the U.S. Government.

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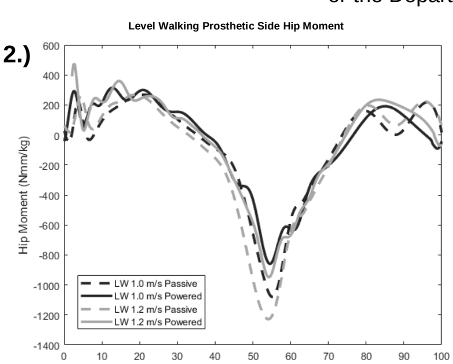

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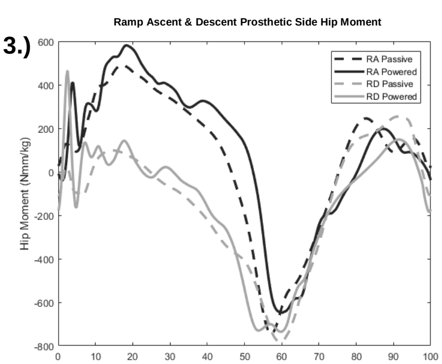


(Left to right): Fig 1: Powered prosthesis and experimental setup; Fig 2: Prosthetic side hip moment for the passive (dotted) and powered prosthesis (solid) during level ground walking at 1.0 m/s (black) and 1.2 m/s (grey); Fig 3: Prosthetic side hip moment during ramp ascent (RA) and ramp descent (RD) at 1.0 m/s

Appendix F: Prosthetic Survey

Subject ID: ____________________________ Date: __________________

Please answer the following questions for your CURRENT prosthesis.

Over the past 4 weeks, please rate your ability in the following activities when using your prosthesis:
"Check ☒ for each statement"

	Unable or hardly able at all (ability < 5%) (0)	High difficulty (ability 5–34%) (1)	Moderate difficulty (ability 35–64%) (2)	Little difficulty (ability 65–95%) (3)	No problems or almost fully able (ability > 95%) (4)
1. To walk	☐	☐	☐	☐	☐
2. To walk in confined spaces	☐	☐	☐	☐	☐
3. To walk upstairs	☐	☐	☐	☐	☐
4. To walk downstairs	☐	☐	☐	☐	☐
5. To walk up a steep hill	☐	☐	☐	☐	☐
6. To walk down a steep hill	☐	☐	☐	☐	☐
7. To walk on sidewalks and streets	☐	☐	☐	☐	☐
8. To walk on slippery surfaces (e.g. wet tile, snow, a rainy street, or a boat deck)	☐	☐	☐	☐	☐
9. To get in and out of a car	☐	☐	☐	☐	☐
10. To sit down and get up from a chair with a high seat (e.g. a dining chair, an office chair)	☐	☐	☐	☐	☐
11. To sit down and get up from a low, soft chair (e.g. a deep sofa)	☐	☐	☐	☐	☐
12. To sit down and get up from the toilet of regular height (no aids)	☐	☐	☐	☐	☐

Subject ID: ___________________________________ Date: ______________________

Please answer the following questions for GT's prosthesis.

"Check ☒ for each statement"

	Unable or hardly able at all (ability < 5%) (0)	High difficulty (ability 5–34%) (1)	Moderate difficulty (ability 35–64%) (2)	Little difficulty (ability 65–95%) (3)	No problems or almost fully able (ability > 95%) (4)
1. To walk	☐	☐	☐	☐	☐
2. To walk in confined spaces	☐	☐	☐	☐	☐
3. To walk upstairs	☐	☐	☐	☐	☐
4. To walk downstairs	☐	☐	☐	☐	☐
5. To walk up a steep hill	☐	☐	☐	☐	☐
6. To walk down a steep hill	☐	☐	☐	☐	☐

User-independent Intent Recognition on a Powered Transfemoral Prosthesis

Log Number: OP150063
Award Number: W81XWH-17-1-0031

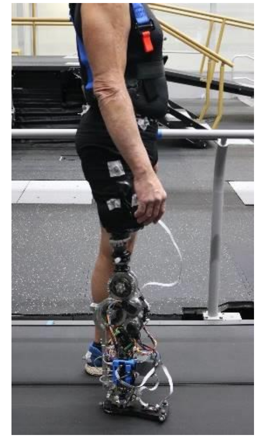
PI: Aaron Young **Org:** Georgia Institute of Technology **Award Amount:** $499,915

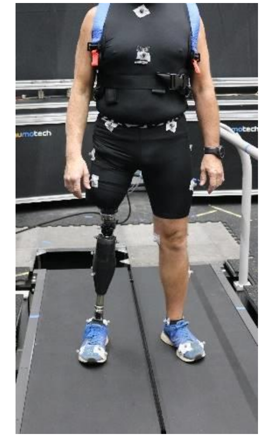
Study/Product Aim(s)

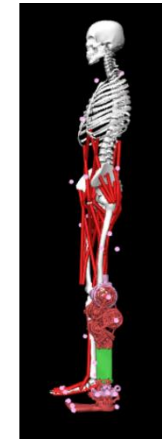
• Compare intent recognition accuracy of the user-independent system to the user-dependent system in real-time as amputees ambulate over different locomotion modes
• Quantify the metabolic cost of walking, amputee biomechanics of motion and completion time and compare between user-dependent and user-independent intent recognition.
• Compare clinical outcome measures of powered prosthesis with active intent recognition to passive prosthesis ambulation.

Approach

We will recruit and train 7 transfemoral amputees on a powered knee/ankle prosthesis and collect from this group a set of sensor data as they ambulate over a locomotion circuit including level walking, stairs and ramps. We will implement our intent recognition systems on the powered prosthesis and test them in real-time and measure metabolic cost of walking, completion time, and user biomechanics and compare to passive prosthesis ambulation.







Accomplishment: We have successfully completed a treadmill based biomechanics protocol on six individuals with transfemoral amputation comparing powered prosthesis to passive device performance. An OpenSim model incorporating the prostheses was developed to analyze 3D locomotion kinematics and kinetics.

Timeline and Cost

Activities CY	17	18	19	20
Subject Recruitment and Fitting				
Training and Data Collection				
System Implementation				
Real-Time Testing				
Estimated Budget ($K)	**$145**	**$75**	**$100**	**$180**

Updated: 2/7/2019

Goals/Milestones

CY17 Goal – Subject Recruitment and Fitting
☑ Obtain HRPO and IRB approval
☑ Fully functional system ready for patient testing

CY18 Goals – Initial Data Collection and System Implementation
☑ Collect sensor data from amputees on level and ramps

CY19 Goal – Real-Time Experimental Testing
☐ Collect sensor data from amputees ambulating over ramps/stairs
☐ Implement intent recognition systems on the powered prosthesis
☐ Real-time tests of intent recognition systems with amputees using the powered prosthesis

CY20 Goal – Finish all remaining tasks
☐ Analyze data and prepare for publication

Comments/Challenges/Issues/Concerns

• We are a few months behind schedule due to lab renovations

Budget Expenditure to Date

Projected Expenditure: $499,915
Actual Expenditure: $200,158.51