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TITLE: User-Independent Intent Recognition on a Powered Transfemoral Prosthesis

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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 and speed of the amputees performing a circuit of locomotion activities including level walking, stairs and ramps. Biomechanics of movement using the controllers will be quantified and compared to passive prosthesis ambulation. Results to date include the development of a second iteration of a powered prosthesis that is more compact, lightweight, and easily adaptable to different users. Various machine learning analyses have been performed to estimate environmental variables from a user-independent perspective. Biomechanical analysis shows how the powered prosthesis can restore similar patterns of gait seen in able-bodied individuals compared to a passive devices. These are promising and strong outcome measures that will be further validated in further stage experiments as the project nears completion.

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: Provide a brief list of keywords (limit to 20 words).

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 – 100% complete

Major Task 4: System Implementation

- Milestone of user-dependent and user-independent intent recognition systems ready for deployment – 60% 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 – 60% complete

What was accomplished under these goals?

Quarter 1 Activities and Accomplishments:

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

A new protocol involving the terrain park was introduced to our cohort of individuals with transfemoral amputation. The protocol involves doing stair and ramp circuits on different stair heights and inclination angles. Preliminary 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/descent, stair ascent/descent) before performing a circuit. For example in a stair circuit, the patients were asked to ambulate overground, transition to stair ascent, transition to level walking, transition back to stair descent, and finally transition back to level-walking. We recorded motion capture data and ground reaction forces for all of trials in order to better understand the underlying biomechanics seen in amputees (i.e. sound side vs. amputated side). 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). We also asked users to ambulate in their prescribed passive prosthesis to begin creating a comparison between active prostheses versus passive devices. Since the previous report, we were able to collect a total of 3 subjects through this protocol, with ongoing data collection happening in the next quarter.

This comprehensive dataset comprising of encoder, inertial measurement units, six-axis loadcell and biomechanics information will be used in helping prepare for System Implementation (see Major Task 4).

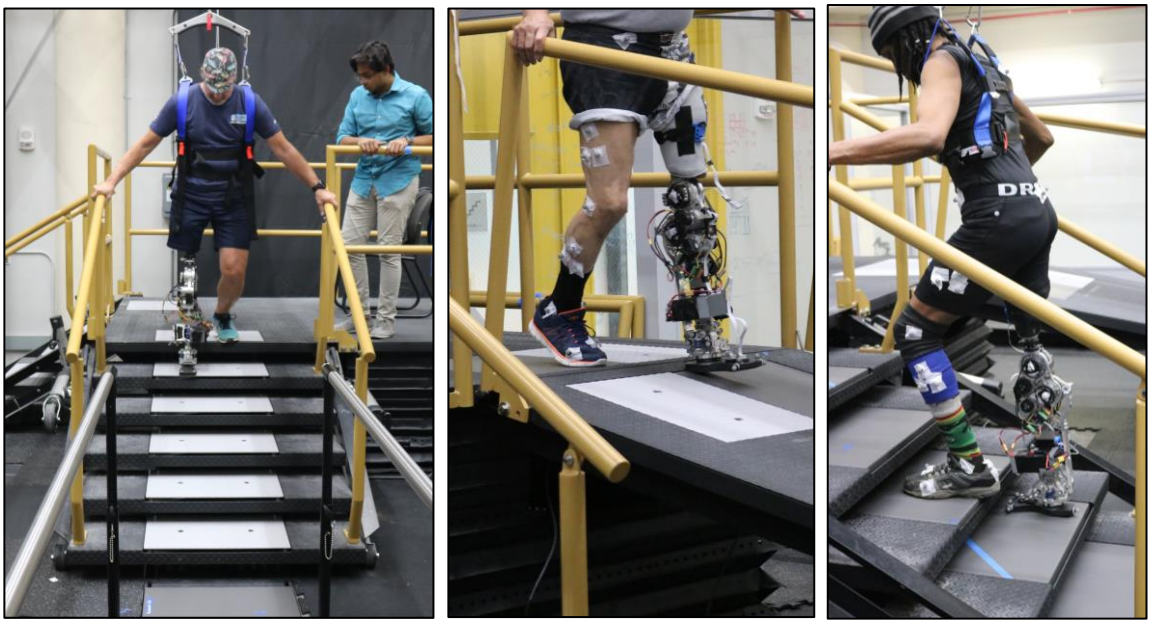


Figure 1: Three different transfemoral participants (K3/K4) walking on the powered leg in the new harness system over force plates embedded on the terrain park. All patients showed great enthusiasm walking with the powered prosthesis, especially on stairs and ramps.

Small updates were made on the device to help make for smoother experiments. Mechanically, new resin printed gears have been added to the device to allow for a more efficient and smoother transfer of power to the user. Improved wire management and shielding was added to mitigate issues in data quality.

Major Task 4: System Implementation

The data collection and control infrastructure developed on the prosthesis forms an excellent basis for real-time prediction of useful environmental variables (i.e. ground slope, stair height, and walking speed). These data can be learned from using machine learning algorithms (i.e. neural networks) to determine the current terrain and its properties. The goal is to use this prediction to alter certain parameters of the device to give more appropriate assistance and improve amputee biomechanics while walking on different terrain.

The primary development work that was done in January-March was to begin developing a method of performing real-time estimation of ground slope and walking speed on board the current embedded system. We have been able to ensure that a prediction can be made fast enough (i.e. < 50 milliseconds) for real-time usage using offline data. Due to some unforeseen issues in data collection with various sensors, a more robust checking algorithm was developed to ensure less post-processing of data is needed. This is important to allow the system to be trained quickly on the same day that a patient is in for testing.

In the last report, mean absolute error (MAE) was used as a metric to determine how usable the predicted output of the regression model would be in predicting ground slope. Since then, we have done further offline analyses by creating separate models for different phases of the gait (Fig. 2). We also validated which machine learning model performs best to estimate these state variables by comparing across four commonly used algorithms (Fig. 3). A neural network architecture showed the best performance by achieving the lowest amount of mean absolute error across stance phase. This result is not surprising as neural network models have an inherent ability of being able to update itself based off of new examples of data and still output relatively low error. Various hyperparameters (number of neurons, learning rate, activation function, etc.) were optimized to maximize the prediction accuracy. Performance was evaluated using the mean absolute error between the estimated and the true output, as an average across subjects with "leave one out" cross-validation across trials. For the ramp experiments, the machine learning error performance as a function of gait phase were 1.22 ± 0.19, 1.23 ± 0.14, 1.50 ± 0.13 and 1.58 ± 0.21 MAE degrees for early stance, late stance, swing flexion and swing extension, respectively. Early stance showed the lowest amount of MAE, showing that this should be a targeted phase of when to do real-time prediction. Both swing flexion and swing extension show larger errors, but this result is not surprising as a key sensor (i.e. 6-DOF loadcell) does not provide useful information when it is not in contact with the ground.

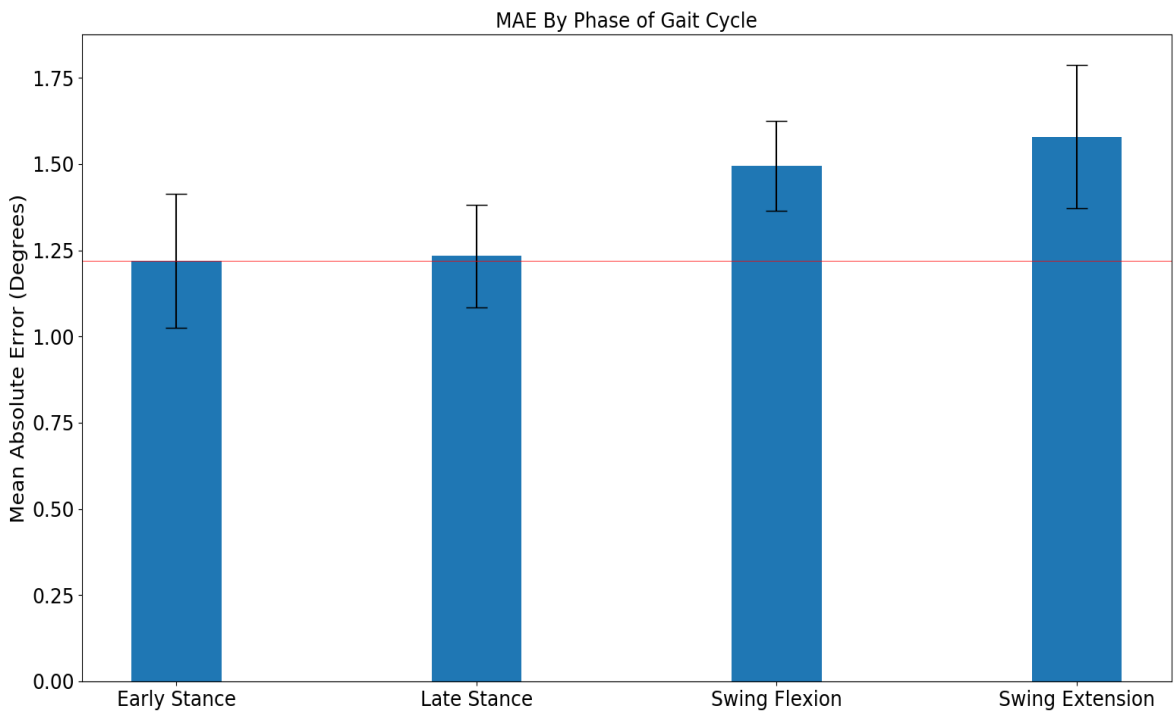


Figure 2: Estimation of ground slope inclination angles using a neural network regressor in 4 different phases in the gait cycle. Stance phase accuracy was better than during swing phase.

Other analyses included finding the optimal feature generation window size to have lowest MAE. By varying the feature generation window size resulted in scores of 1.31 ± 0.17, 1.27 ± 0.18, 1.22 ± 0.19 and 1.26 ± 0.21 degrees for 50, 100, 250 and 500ms. According to these results, slope prediction will see the best performance if estimated during early stance using the past 250 milliseconds of data.

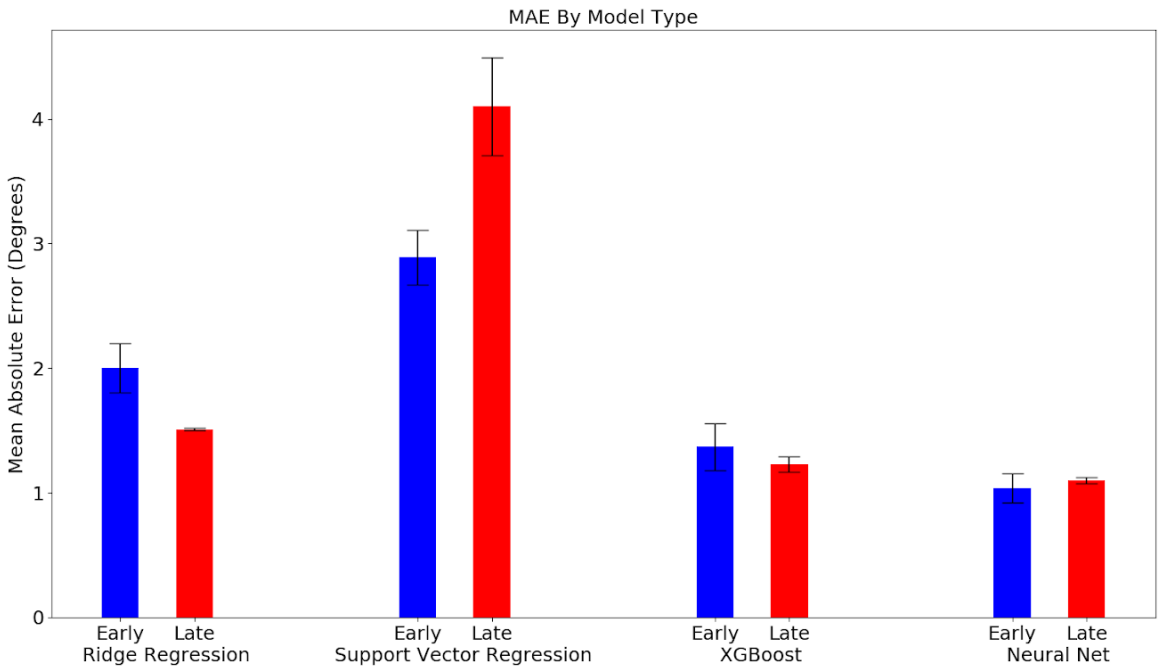


Figure 3: Model selection of different machine learning algorithms when trained in both early and late stance phases. Neural networks should the lowest amount of mean absolute error in both phases compared to ridge regression, support vector machines and XGBoost.

We wanted to ensure that there is no single class of data had unusable error. In one ramp circuit, there are three different modes the user is in per trial (level walking – LW, ramp ascent – RA, ramp descent – RD). Data was separated for each mode and for both early stance and late stance phases (Fig. 4).

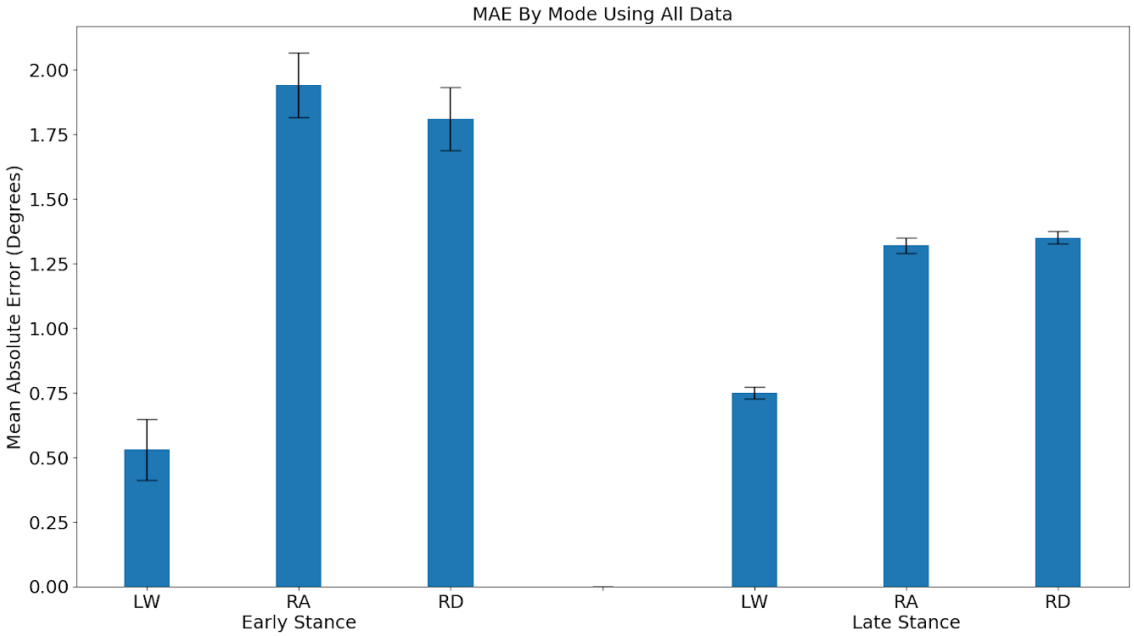


Figure 4: Comparison of error in each separated mode in both early and late stance phases of the gait cycle. LW=level walking, RA=ramp ascent, RD=ramp descent

The results from Fig. 4 shows that the lowest mean absolute error occurs in the level walking steps. When the MAE is averaged across the three different modes, the results can be skewed due to sample size available in each mode (LW has the most examples). A further analysis of creating independent models with each phase and mode was performed, but MAE did not change significantly. Also this result validates that only 1 model is necessary per phase which reduces the complexity of implementing this in real-time. The next step was to see if there were additional post-processing steps to further reduce the error seen specifically in ramp ascent and ramp descent. After further optimization, and the inclusion of additional subjects (N=5 presently for our ramp data collection), we were able to achieve the errors displayed in Fig. 5.

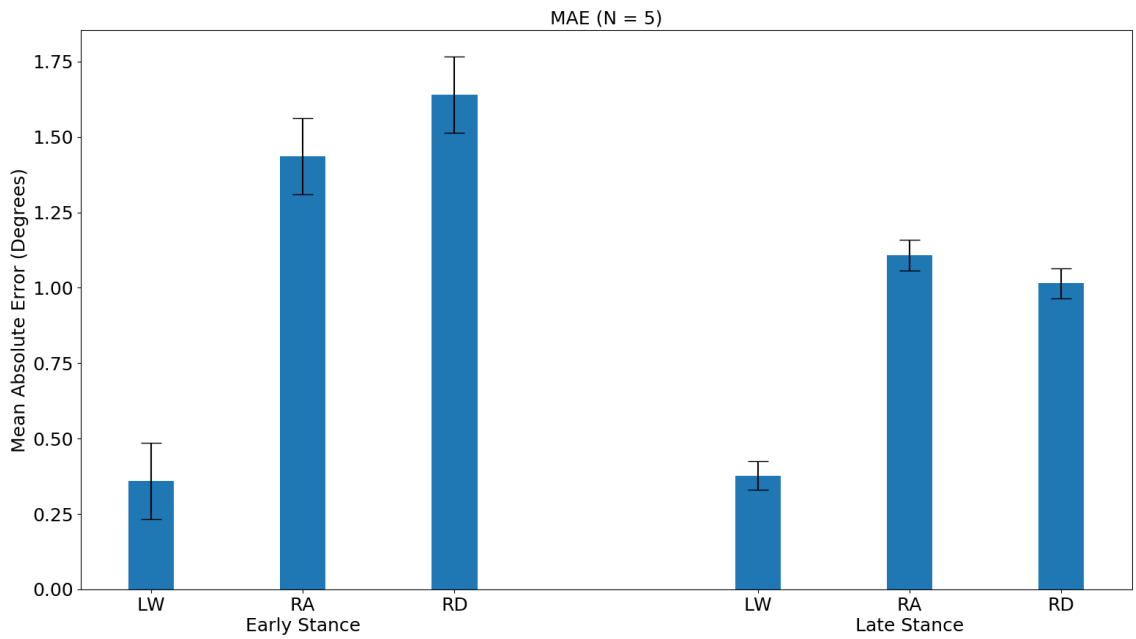


Figure 5: Comparison of error in each separated mode in both early and late stance phases of the gait cycle after raw data was processed in a more optimized fashion. LW=level walking, RA=ramp ascent, RD=ramp descent

We have also begin comparing how a real-time machine learning algorithm will be able to output a prediction in a timely but accurate fashion. Figure 6 shows what an estimated output looks like for a ramp circuit in some offline analyses. These results show that we are close to making an implementable real-time system that can be embedded on our electronics system in a seamless manner. By adding a Kalman filter after a model has been optimized based off of its hyperparameters can help further reduce the prediction noise to give a more smooth output. The Kalman filter is helpful because of its ability to make an educated guess about the next state given prior information. Since the algorithm does not require a lot of prior history, it is a useful tool that can be used in real-time embedded systems.

Another type of user state information, we are trying to predict is walking speed. Users (N=6) were asked to walk on a treadmill for 60 seconds for each static speed ranging from 0.5 m/s to their maximum preferred walking speed (0.9 to 1.1 m/s) in increments of 0.05 m/s. A similar phase analysis was also performed for this walking speed protocol.

The machine learning error performance as a function of gait phase were 0.025 ± 0.026, 0.029 ± 0.029, 0.040± 0.038, and 0.042 ± 0.040 m/s for early stance, late stance, swing flexion and swing extension, respectively (seen in Fig. 7 for N=4 subjects processed to date). The results also indicate that the best performance on average can be achieved in the early stance phase of the gait cycle. This dataset will also be analyzed in more depth (we have collected N=6), and results will be included in future reports.

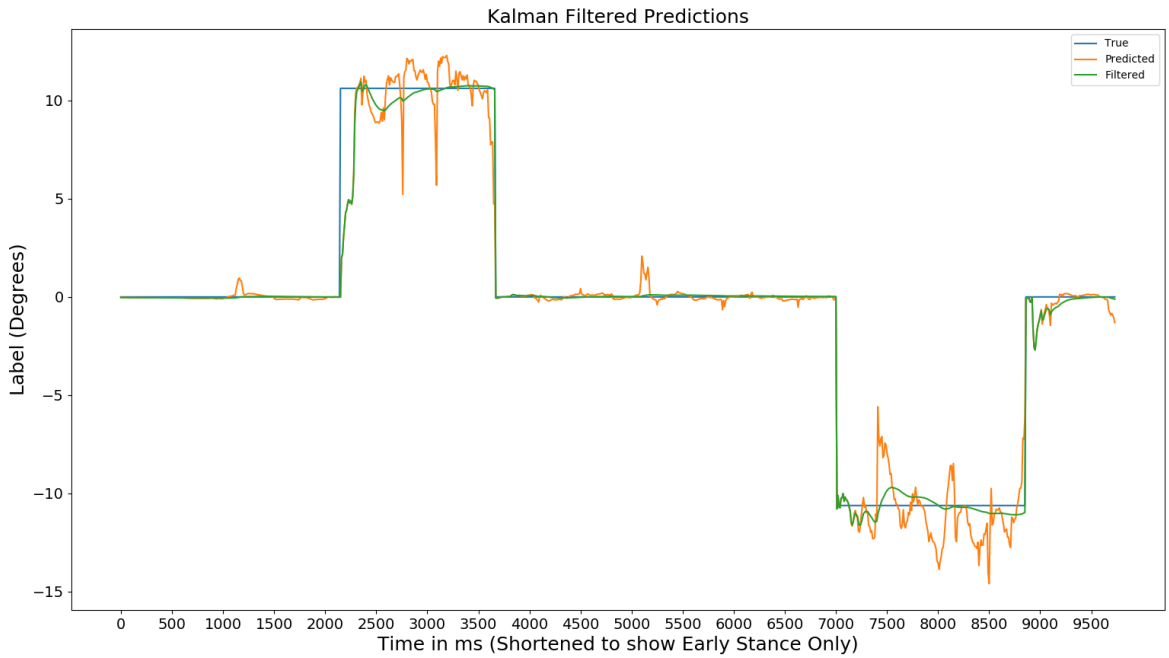


Figure 6: Comparison of raw prediction and Kalman filtered prediction versus ground truth of inclination angle in a ramp circuit in early stance.

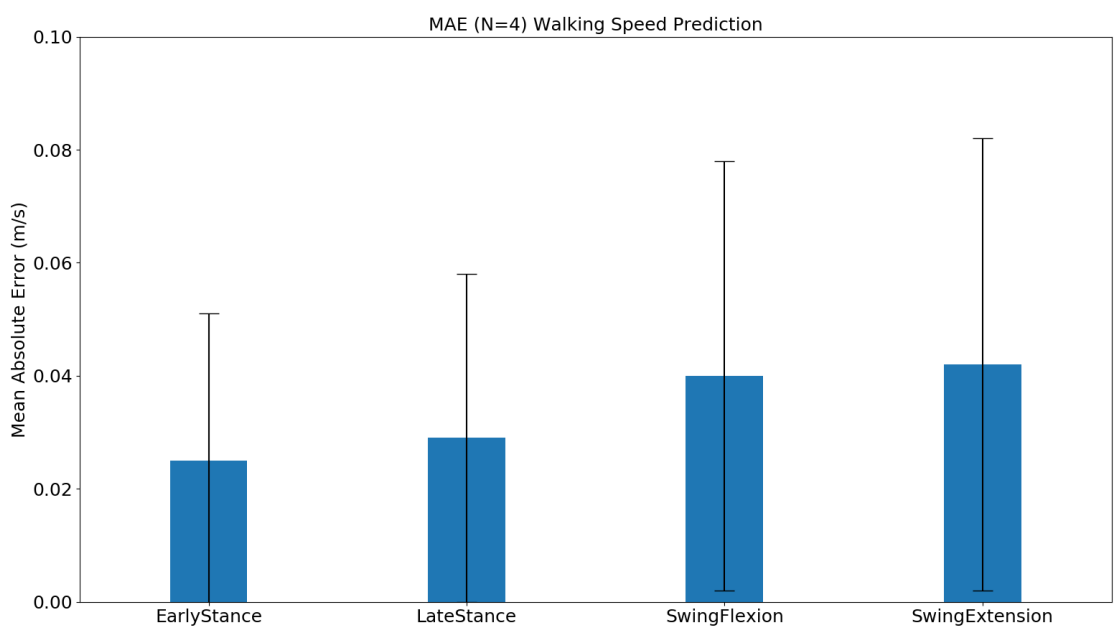


Figure 7: Estimation of walking speed using a neural network regressor in 4 different phases seen in the gait cycle.

We have also submitted an abstract in February to the Military Health System Research Symposium (MHSRS) conference to showcase our ability to create accurate machine learning algorithms to predict ground slope and walking speed based on embedded sensors on the powered prosthesis. 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.

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

Last quarter, 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. 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.

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. A passive model was also developed in OpenSim to ensure a direct comparison can be made between the different prostheses (Fig. 8). We will continue to analyze biomechanics data and report on these in more detail in a future report.

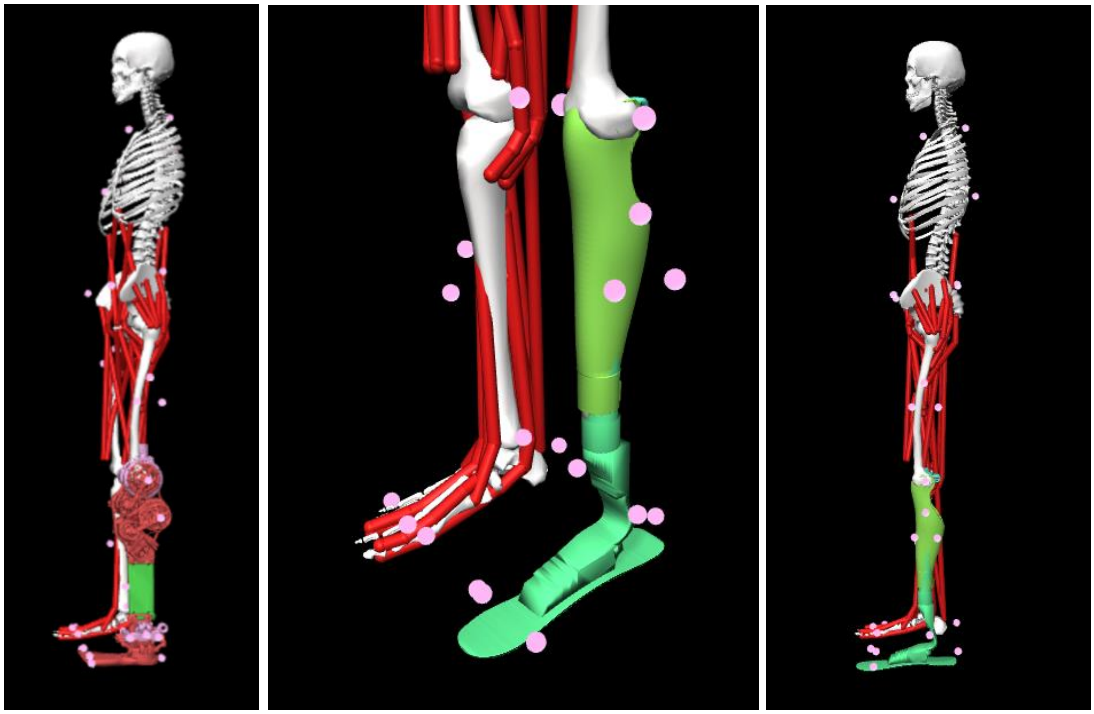


Figure 8: OpenSim models created in order to better perform biomechanical analysis of calculating kinematics and kinetics using forceplates and motion capture for both powered versus passive prostheses.

Preliminary results of inverse kinematics have been outputted using the OpenSim pipeline (Fig. 9). The data shows how active prosthesis is able to provide a more biological knee kinematic profile compared to the passive prosthesis for level ground walking. Key characteristics of the powered device include excellent swing flexion clearance of 60 degrees (similar to an intact leg) and slightly more stance phase knee flexion. Note: we generally make the leg quite stiff similar to a passive device during early-mid stance phase, so it's not surprising that we do not see a loading response completely similar to a biological leg, which would exhibit ~20 degrees knee flexion rather than just 10-12 degrees as seen with the powered leg.

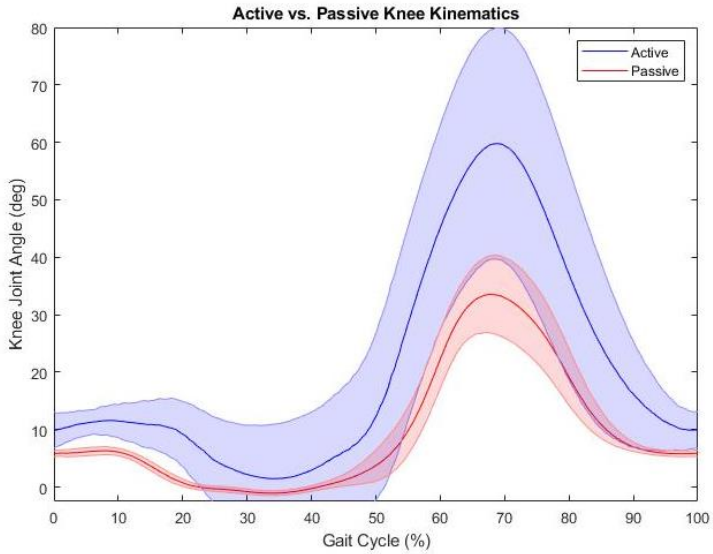


Figure 9: Knee kinematics for both active and passive prostheses when walking on a force-instrumented treadmill

Quarter 2 Activities and Accomplishments:

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

From the last quarter, we had introduced a new protocol using our terrain park to better understand the underlying biomechanics seen in persons with amputation (i.e. amputated side vs. sound side). Users were asked to perform different ramp and stair circuits at different inclination angles and step heights. A circuit consisted of ambulating overground and transitioning to a ramp or staircase and returning back to the original position. We recorded motion capture data and forceplate data to better understand amputee gait on both our prosthesis and their respective daily prosthesis (See Major Task 6). We have completed a total of N=5 subjects on both the powered and passive protocol for overground walking, ramps and stairs. The other two subjects are half way done (finished passive) but still need another session to finish powered during this next quarter. Mechanical sensors (i.e. encoders, IMU's, six-axis loadcell) onboard the device will be used to help further develop our intent recognition systems (see Major Task 4).

In our previous report, we noted that we were invited to submit a journal paper to our MHSRS submission to the MHSRS 2018 Supplements. This paper has been tentatively accepted and will be provided as a supplement in a future report once it is in final form. Small updates were made on the device to help allow for smoother experiments. Improved wire management and shielding was added to mitigate issues in data quality. Validation of motion capture marker placement for our prosthesis and a passive prosthesis was performed to ensure a decent framework for biomechanical comparison analysis can be achieved (See Major Task 6).

Major Task 4: System Implementation

The data collection and control infrastructure developed on the powered prosthesis forms an excellent basis for real-time prediction of useful environmental variables (i.e. ground slope, stair height, and walking speed) to help improve functionality of using a wearable robotic device. These data can be learned from using machine learning algorithms (i.e. neural networks) to determine high level information such as current terrain mode or continuous estimation of what type of ramp grade a user may be ambulating on. The goal is to use this prediction to alter certain parameters of the device to give more appropriate assistance and improve amputee biomechanics while ambulating on different terrain.

The main development done for system implementation between April – June was to begin developing our framework for doing a rigorous machine learning analysis for different tasks (i.e. state estimates for walking speed, slope angle, or stair height). We have updated some of our firmware on the device to help alleviate prior issues seen with quality of data as well reduce post-processing of data.

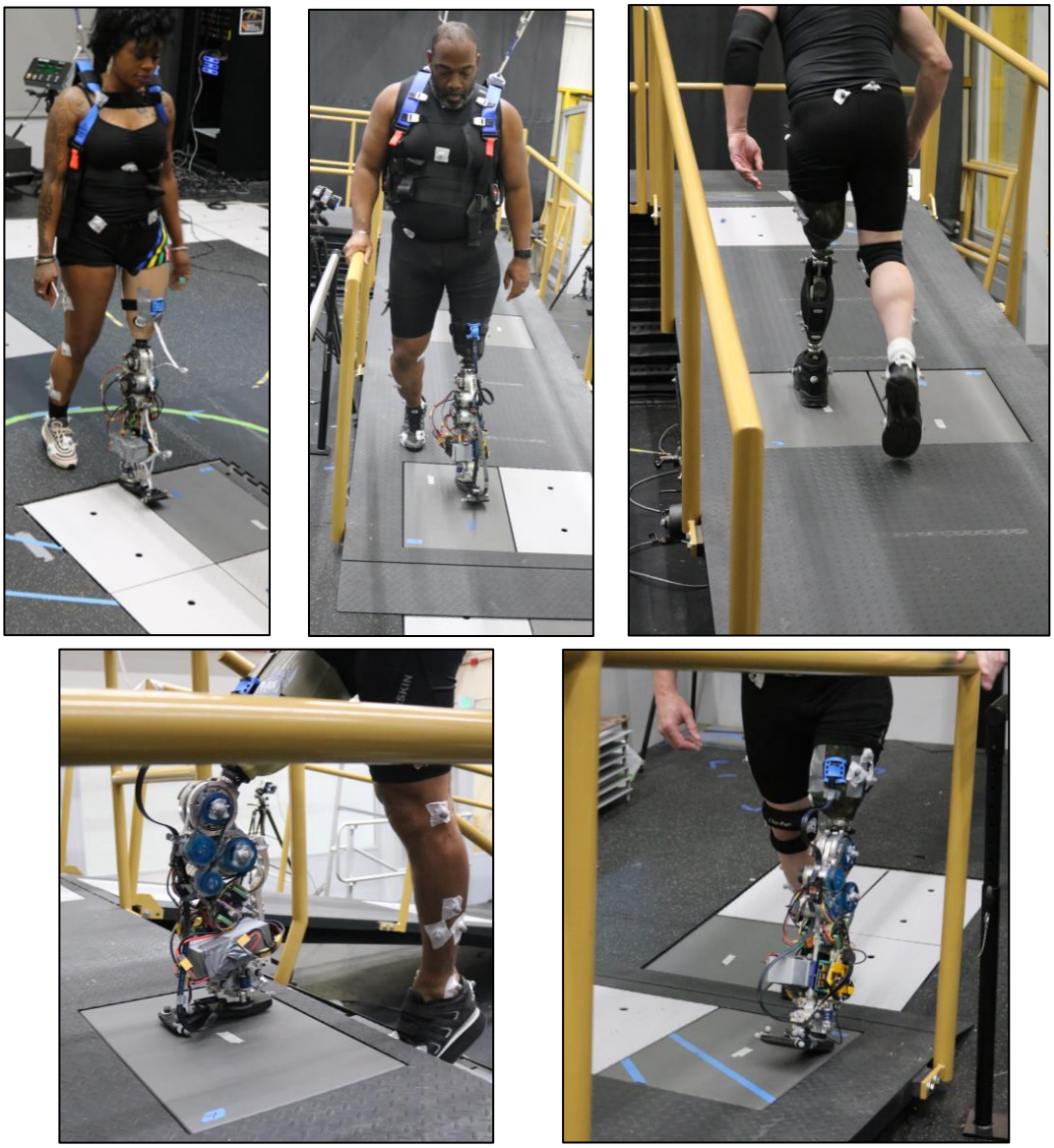


Figure 10: Four different transfemoral participants (K3/K4) walking on the powered vs. passive leg in the new harness system over force plates embedded on the terrain park. All patients were excited to ambulate with our powered prosthesis across a variety of walking tasks.

In the last report, mean absolute error (MAE) was used as a metric to determine how usable the predicted output of the regression model would be in predicting ground slope and walking speed. Previous results showed that early stance showed the lowest amount of MAE, implying that this should be a targeted phase of when to do real-time prediction. Both swing flexion and swing extension showed larger errors, but this result was not surprising as a key sensor (i.e. 6-DOF loadcell) did not provide useful information when not in contact with the ground. Since then, we have done further offline analyses by doing a “leave-one-out” sensor feature selection sweep for ground slope to understand their contribution to performance of the state estimation (Fig. 11).

This allows for us to determine which sensor is most critical to model prediction. For walking speed we ran a "remove-one-speed" analysis to determine whether a neural network can interpolate between different walking speed conditions to provide a decent predicted state estimation in a continuous manner.

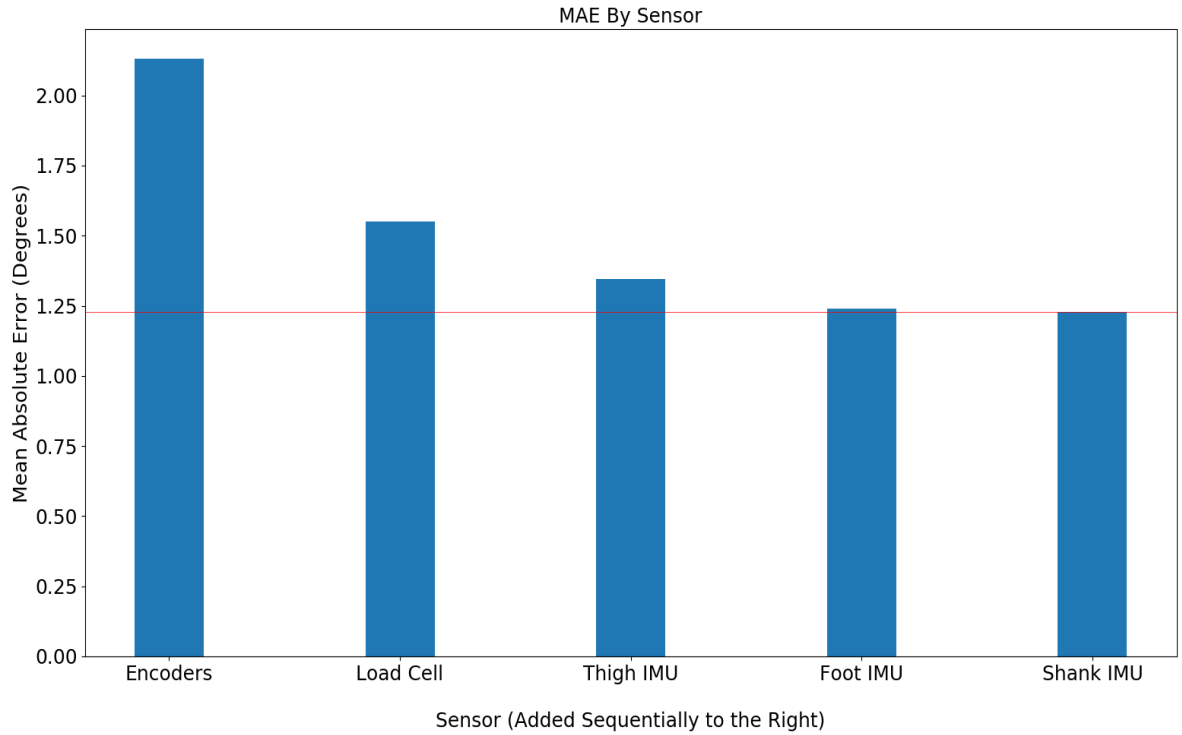


Figure 11: Determining rank of sensors in providing best estimation of ground slope inclination angles using a neural network regressor specifically in early-stance using leave-one-out sensor elimination. Removing the encoders show the highest MAE implying that this is most important mechanical sensor in helping reduce error seen in our state estimation.

Another type of user state information, we are trying to predict is walking speed. Users (N=6) were asked to walk on a treadmill for 60 seconds for each static speed ranging from 0.5 m/s to their maximum preferred walking speed (0.9 to 1.1 m/s) in increments of 0.05 m/s. In the previous report, we performed a phase analysis with a neural network to determine the best timing during the gait cycle of predicting the useful environmental variable. Since then, we performed a "remove-one-speed" validation to understand whether a machine learning algorithm can generalize and interpolate across unknown speeds not seen in the training data (Fig. 12). The average MAE across all subjects (N=4) and across different walking speeds seen between 0.55 m/s through 0.9 m/s was 0.0352 (*error is in units of m/s*).

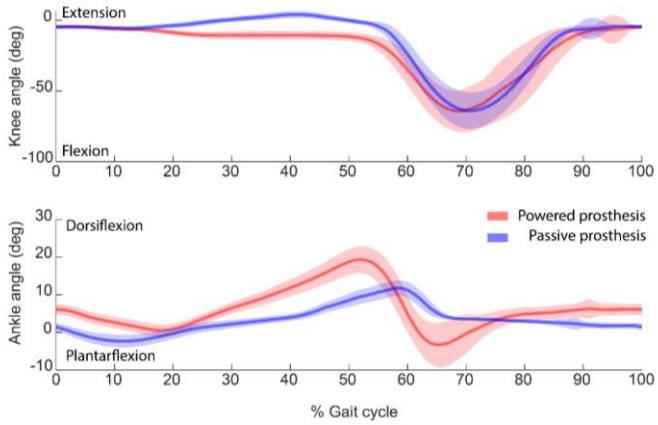
Figure 12: Comparison predicted speed versus actual speed across walking speeds. This figure shows that our machine learning algorithm (neural network) is able to generate accurate state estimates of unknown walking speeds under our trained range of speeds.

We have also been accepted to present our abstract in Military Health System Research Symposium (MHSRS 2019) conference to showcase our ability to create accurate machine learning algorithms to predict ground slope and walking speed based on embedded sensors on the powered prosthesis (see Appendix B). 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.

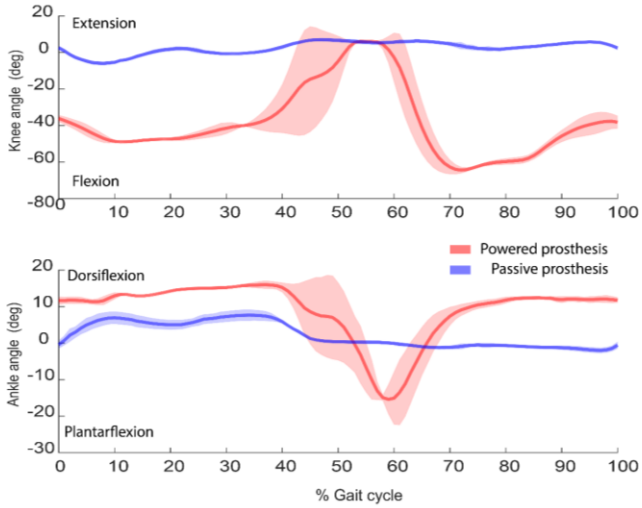
Major Task 6: Comparison of clinical parameters of powered prosthesis compared to passive prosthesis

Between April – June, the primary development was focused on improving the biomechanical analysis between our powered prostheses compared to individual's respective passive prosthesis using the OpenSim platform. In our last report, we mentioned that we had developed and configured several models in order to begin performing inverse kinematics and dynamics for both our powered and passive prostheses. Since then, an inverse kinematic analysis was performed on our treadmill walking data that did a comparison between powered and passive prosthesis ambulation with our cohort of individuals with transfemoral amputation (N=6). We formally collected bilateral biomechanical data (including motion capture and split-belt force-instrumented treadmill) while asking users to perform level walking, slope ascent, and slope descent walking. Our results depict kinematic plots across these different ambulation modes (Fig. 13). Furthermore, renders of both active and passive prostheses in our simulated musculoskeletal environment were generated to better visualize amputee gait walking patterns (Fig. 14).

Level Walking



Slope Ascent



Slope Descent

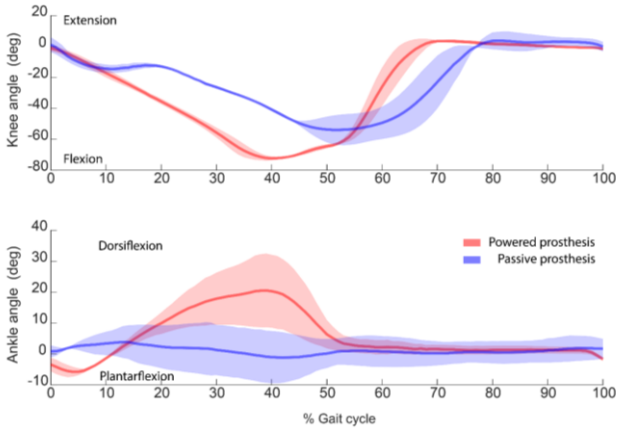


Figure 13: OpenSim inverse kinematics of the both the powered versus passive prosthesis models in level walking (top), slope ascent (middle), and slope descent (bottom). Results show that powered device are able to generate improved gait similarities seen in able-bodied individuals.

Preliminary results of inverse kinematics have been outputted using the OpenSim pipeline (Fig. 13). For level walking, the data shows how active and passive prostheses have similar biological knee characteristics. Note: we generally make the leg quite stiff similar to a passive device during early-mid stance phase, so it's not surprising that we do not see a loading response completely similar to a biological leg, which would exhibit ~20 degrees knee flexion as seen in loading response. However, a key characteristic of the powered device is that it is able to generate push-off at the ankle which is useful for propelling the user moving forward without having to perform other compensatory movements (i.e. hip hike or hip abduction/adduction). In slope ascent, the active device allows for controlled knee movement compared to the passive device where it needs to be locked in an extended manner to ambulate. Similarly, the ankle is able to provide more torque in order to generate net positive power. In the slope decent figure, the powered device is allowed to be more compliant and can be adjusted to user preference of how "stiff" they want the leg to act as step-over-step ramp descent is performed.

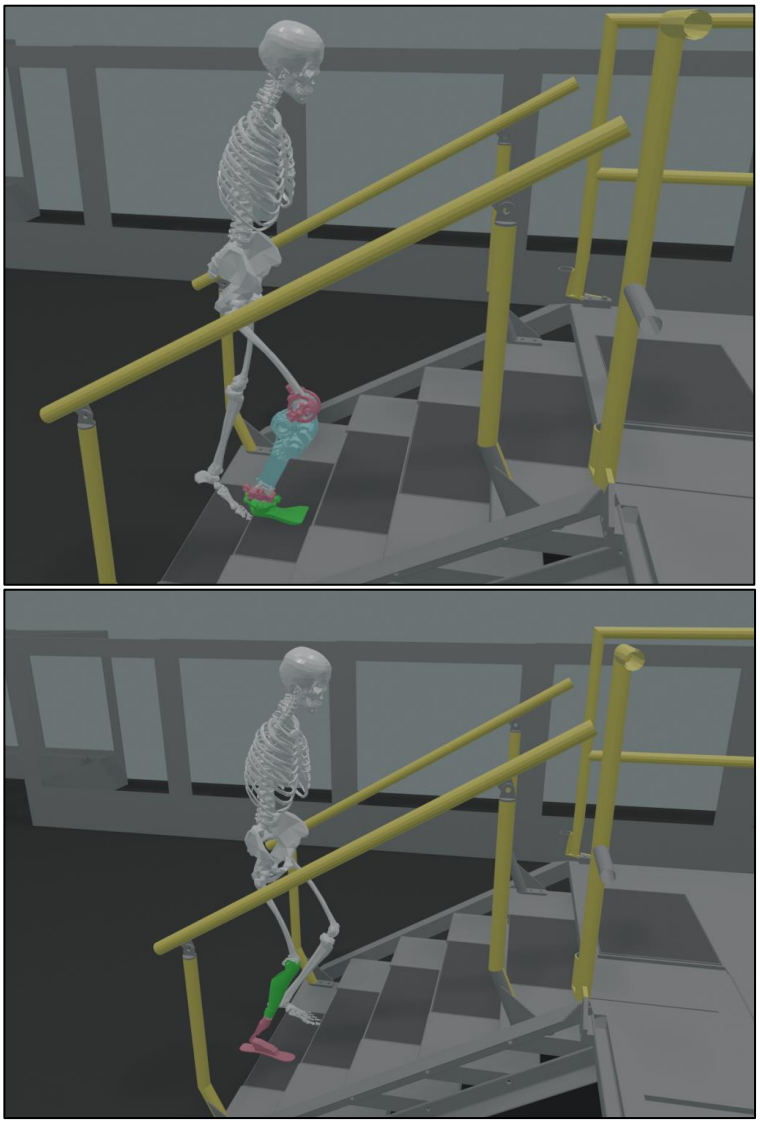


Figure 14: Renders for powered (top) and passive (bottom) prostheses were created to better visualize how different gait patterns are performed based off results generated through OpenSim pipeline.

Quarter 3 Activities and Accomplishments:

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

We completed a significant experiment involving level ground walking, stairs and ramps this quarter from N=7 patients. We also collected data using our terrain park to better understand the underlying biomechanics seen in persons with amputation (i.e. amputated side vs. sound side). Users were asked to perform different ramp and stair circuits at different inclination angles and step heights. A circuit consisted of ambulating overground and transitioning to a ramp or staircase and returning back to the original position. We have finished this protocol for a total of N=7 subjects on both the powered and passive protocol for overground walking, ramps and stairs. We recorded motion capture data and force plate data to better understand amputee gait on both our prosthesis and their respective daily prosthesis (See Major Task 6). Embedded mechanical sensors (i.e. encoders, IMU's, six-axis loadcell) onboard the device will be used to help further develop our intent recognition systems (see Major Task 4).

Our journal submission to the MHSRS 2018 Supplements was accepted this quarter. This paper will be provided as a supplement in a future report once it is available in its final form. Small updates were made on the device to help allow for smoother experiments. New PCB's were manufactured to make our electronic system as compact as possible and easy to collect data. Another modification is that we have increased our range of motion of the knee joint to allow for subjects to easily transition between sit and stand as well as make it easy to ambulate during stair collection trials (See Major Task 4).

Major Task 4: System Implementation

Between July – September, one of the focuses was improving the mechanical design of the current leg and finish manufacturing the new open source leg. The range of motion for the knee joint on the current prosthetic device was increased from 70 degrees to 90 degrees. This will allow for users to sit more comfortably and naturally with the device. With this increased amount of flexibility, users will be able to more easily walk up stairs due to its ability to flex and clear the step across different stair heights. Lastly, our machining mall was able to complete the manufacturing of our new prosthetic device. Major features of this device is that it much lighter than our first version, most of the transmission and wires are enclosed with our actuator packages to ensure good wire management, and ability to easily adjust heights to the exact desired height needed for each subject. The previous design only allowed for 1 cm increments, but with this design we can achieve any height required to ensure that the user feels as comfortable as possible.

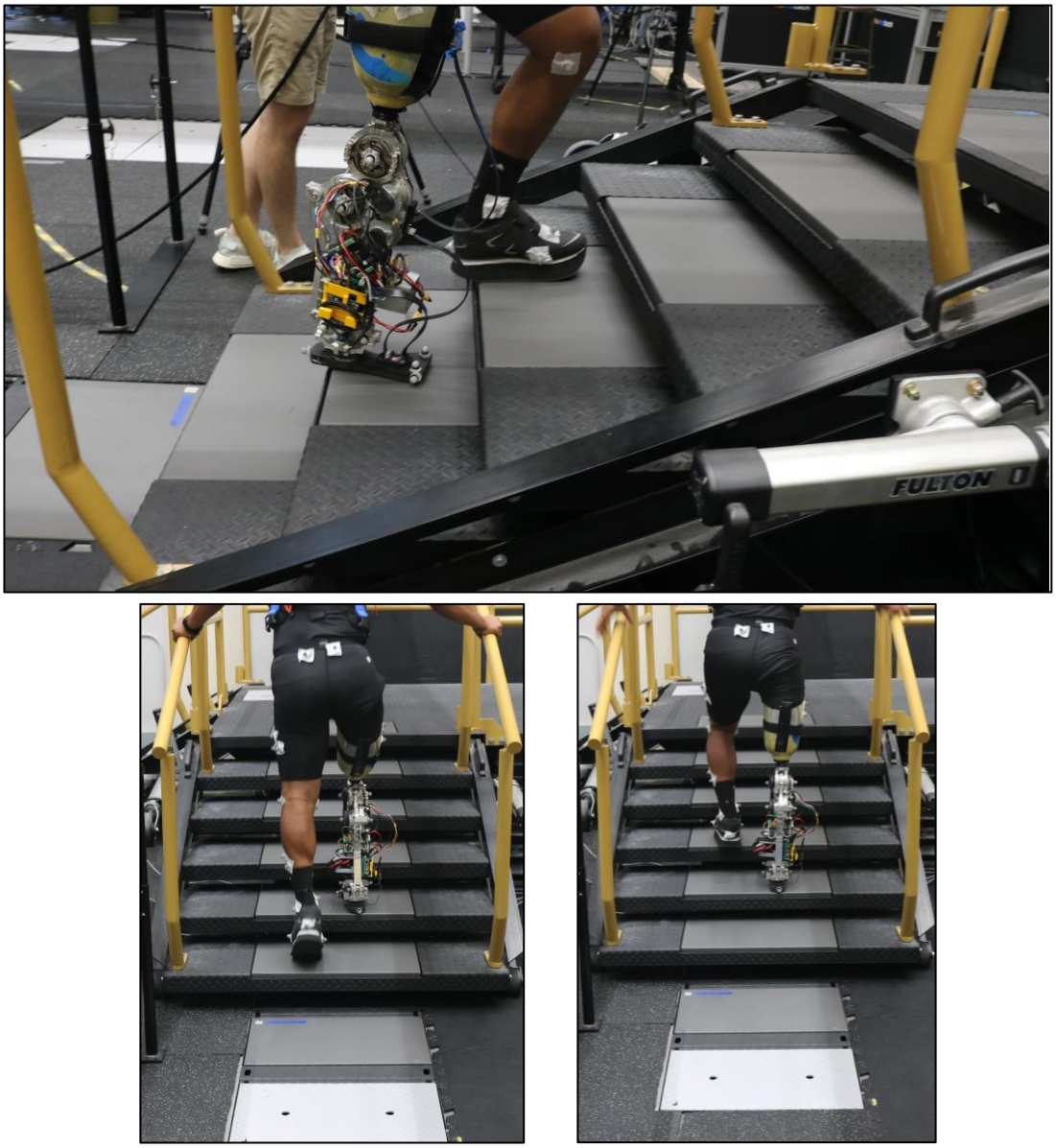


Figure 15: One of our last subjects (K4 – ambulation level) to complete this initial terrain park experiment. Feedback from the user indicated that the powered prosthesis was definitely more comfortable for ascending stairs.

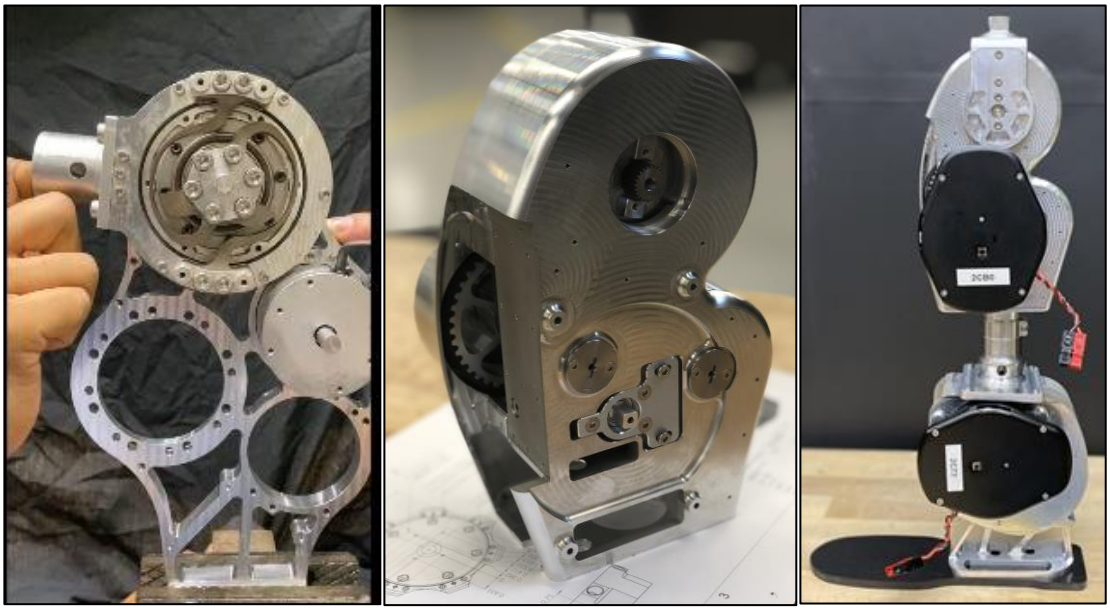


Figure 16: Modification to the main frame to allow for 0-90 degrees of rotation at the knee joint (Left), knee assembly of the new open source leg (middle), and final assembly of the entire prosthetic device with the actuators attached (right).

From the data now collected from all of the terrain park experiments, we now have the ability develop smarter control strategies by applying machine learning algorithms to both predict and estimate useful environmental variables (i.e. ambulation mode, walking speed, ground slope, and stair height). By using embedded sensors on the powered prosthesis as well as our control infrastructure allows us to have a solid foundation for having real-time prediction/estimation. We have continued to build a pipeline for creating machine learning algorithms that learn on these different tasks. For future studies, the goal is to use these predictions to alter certain control parameters to modulate assistance and improve amputee biomechanics across a variety of walking modes. The major development was ensuring that our framework was robust in order to perform rigorous machine learning analyses for different tasks. Our pipeline developed goes from taking our raw data, extracting feature tables, training models, and testing out our machine learning algorithms (Fig 17).

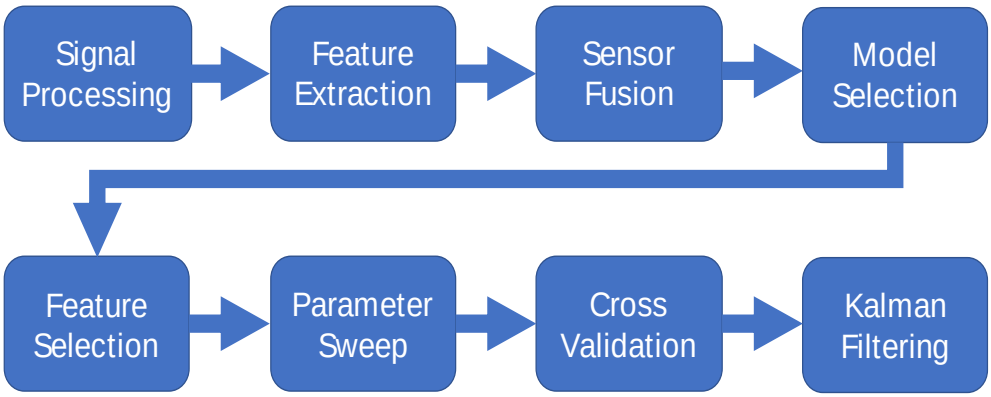


Figure 17: Machine learning flow chart of using standard machine learning techniques to create models capable of predicting & estimating useful environmental variables

We also presented our abstract in Military Health System Research Symposium (MHSRS 2019) conference to showcase our ability to create accurate machine learning algorithms to predict ground slope and walking speed based on embedded sensors on the powered prosthesis (see Appendix B). We will continue to develop our machine learning toolbox and optimize our algorithms in the next quarter to generate implementable models that can be utilized in real-time.

We have also started enhancing our control system by looking at how to scale impedance parameters as a function of environmental variables. From a different dataset we collected in lab, we have computed inverse kinematics and kinetics for able-bodied individuals. We are using the dataset to understand which part(s) of the gait cycle get affected by both walking speed and ground slope. We have been able to see that ankle push off is a good correlate to walking speed (Fig. 18). Hence we will creating scaling equations and begin testing these different control strategies in future quarters to enhance the powered prosthesis's ability to effectively provide appropriate assistance to more "real-world" tasks.

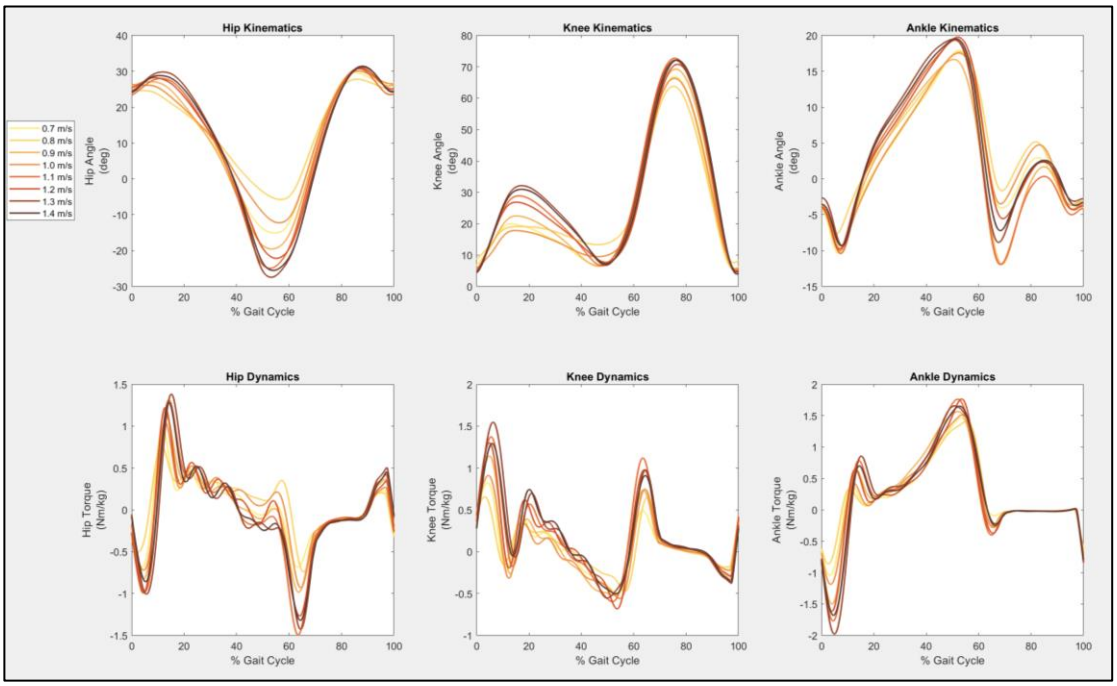


Figure 18: OpenSim computed inverse kinematics and kinetics across different walking speeds. This data gives a baseline for creating new scaling equations.

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

Between July - September, we finalized our dataset of N=7 subjects walking with both the powered and passive devices across the different ambulation modes (overground, slopes, and stairs). We formally collected bilateral biomechanical data which included motion capture and embedded force plate data. We are in the current process of analyzing this data will show both inverse kinematics and kinetics results in the next report across all the different modes. We have shown our modeling techniques and preliminary results in previous reports and will have a complete analysis completed for the next annual report.

Quarter 4 Activities and Accomplishments:

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

The main mechanical development that has been done in the last several months is to have our new iteration of our powered leg assembled and able to easily fit our able-bodied adapter and different individuals with transfemoral amputation. The open-source leg received a coat of anodization to prevent any corrosion from occurring. Furthermore, the custom control system embedded in the actuator packages were integrated with our control architecture. At the end of the last quarter, a pilot test was performed where a user was able to ambulate across all five locomotion modes (level walking, ramps, and stairs) on our terrain park.

Analysis of data from the old leg has enabled us to better understand the underlying biomechanics present in ambulating stairs (See Major Task 6). Different machine learning algorithms have been explored to estimate user state and environment information such as mode classification and continuous regression tasks such as walking speed and slope estimation (See Major Task 4).

Major Task 4: System Implementation

From the data now collected from all of the terrain park experiments, we now have the ability develop smarter control strategies by applying machine learning algorithms to both predict and estimate useful environmental variables (i.e. ambulation mode, walking speed, ground slope, and stair height). A focus of this last quarter was to start developing machine learning algorithms that could generalize across different users (i.e. user independent). In addition, by using embedded sensors on the powered prosthesis as well as our control infrastructure allows us to have a solid foundation for having real-time prediction/estimation. We have continued to enhance our machine learning pipeline especially for implementing real-time models on a microprocessor. Three different tasks were analyzed which include user-independent walking speed estimation, user-independent mode classification, and user-independent and walking speed independent slope estimation. The last task is a preliminary analysis to show that a machine learning algorithm is able to distinguish between a combination of terrain changes and speeds to be more robust for more "real-life" scenarios.

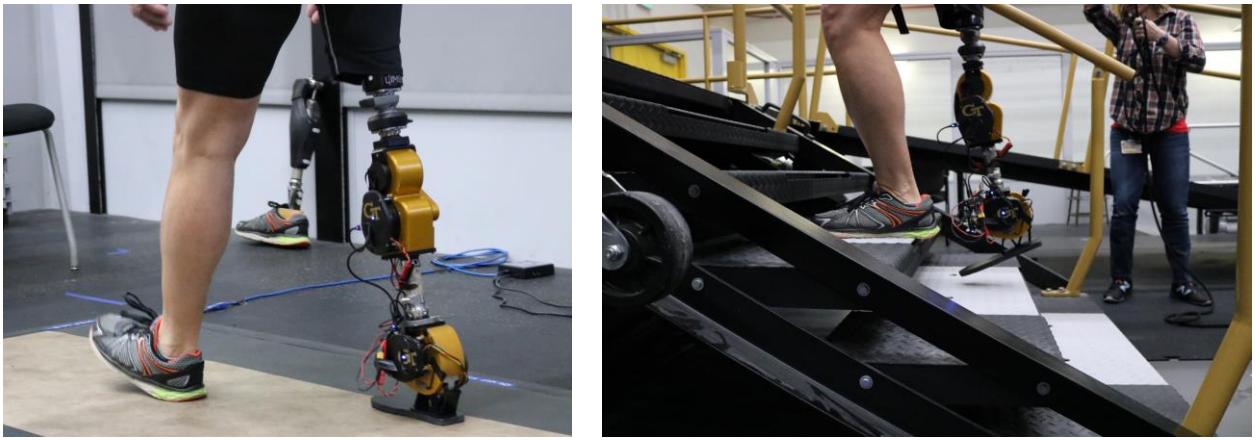


Figure 19: Pilot experiment that was performed with the new OSL device with a K4 individual. Feedback from the user indicated that this new device was easier to use due to its reduced weight and compactness.

A model comparison was performed on estimating walking speed using embedded sensors on the powered prosthesis. The sensor information that was utilized from the prosthesis include two joint encoders, a six-DOF loadcell, and 2 inertial measurement units (IMUs) located at the foot and shank of the device. It can be seen that the lowest average MAE when training an user-independent model across all subjects (N=6) and across different walking speeds seen between 0.50 m/s through 0.9 m/s was 0.096 ± 0.006 (*error is in units of m/s*). From a preliminary analysis, ensemble machine learning algorithms seem to perform better across users. Future work of more rigorous optimization may yield lower errors.

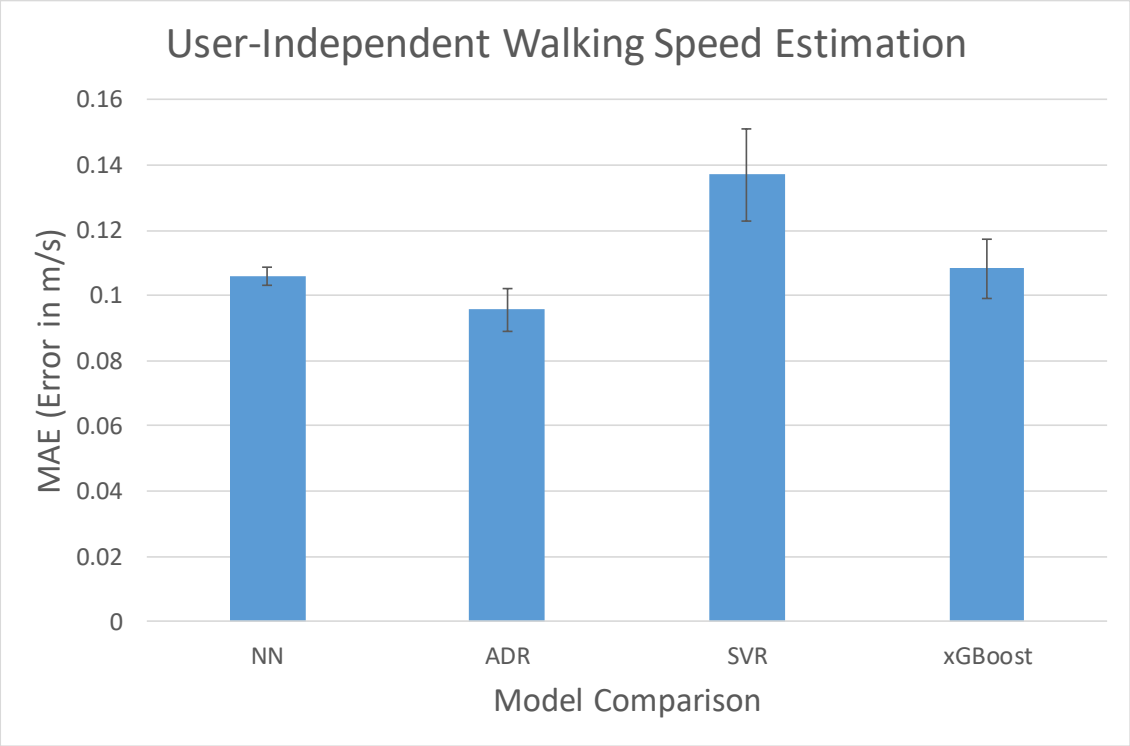


Figure 20: Four different models were trained to understand which type of machine learning algorithms can best generalize across users. Ensemble learning models showed lowest error when comparing mean absolute errors across a range of walking speeds. These algorithms show potential in being able to estimate environmental information that can be used in enhancing prosthetic controllers.

A focus on real-time implementation on our microprocessor was performed in this last quarter. Specifically, creating a feature extractor and predictor that would be within the bandwidth of our control system. Since our code base was easily translatable to the new leg, all functionality built to date was easily accessible on our new iteration of the leg. We were successful in achieving a high level controller update rate of 50 Hz in which we can output a decision every 20 milliseconds for our mode classifiers. A validation was done by creating a user-dependent model using sensor information collected on the new leg. Results show that steady state error is less than 1%. This is promising as we continue to progress to building a user-independent system that can generalize across users. Future work will look at creating machine learning tiers of predicting and estimation user and state information (i.e. classification and regression simultaneously occurring).

Another dataset we had collected alongside the main prosthesis experiment was performed to develop a speed and user-independent slope estimator for applications for real-time lower-limb prosthetic control. We completed a 10-subject experiment involving walking across static inclines (-15 to 15 degrees) at varying speeds (0.6 to 1.4 m/s) for each incline. Able-bodied subjects were suited with inertial measurement units (IMUs), goniometers, and motion capture markers. Ground reaction forces were captured via a Bertec instrumented treadmill. The collected sensor data was sectioned off to represent sensor suites commonly found in ankle prostheses, knee-ankle prostheses, and hip exoskeletons. Our goals are to develop a slope estimator for each sensor suite that would enable wearable assistive devices to appropriately scale joint torques.

In our initial analyses, we chose to compare the slope estimation performance of 2 machine learning models (neural networks and XGBoost). These models were chosen as starting point using results found from earlier slope estimation analyses seen in previous reports. Each gait cycle was divided equally into single-phase ("_1"), double-phase ("_2"), triple-phase ("_3"), and quadruple-phase ("_4") gait cycles to explore if there was a phase-dependency present. Models were trained for each gait cycle subdivision to identify the optimal "time" to estimate incline angles. Preliminary results show that ankle prosthesis sensors could estimate incline angles with errors as low as 1.3 degrees. The lowest errors occurred during 25-50% of the gait cycle with the XGBoost algorithm.

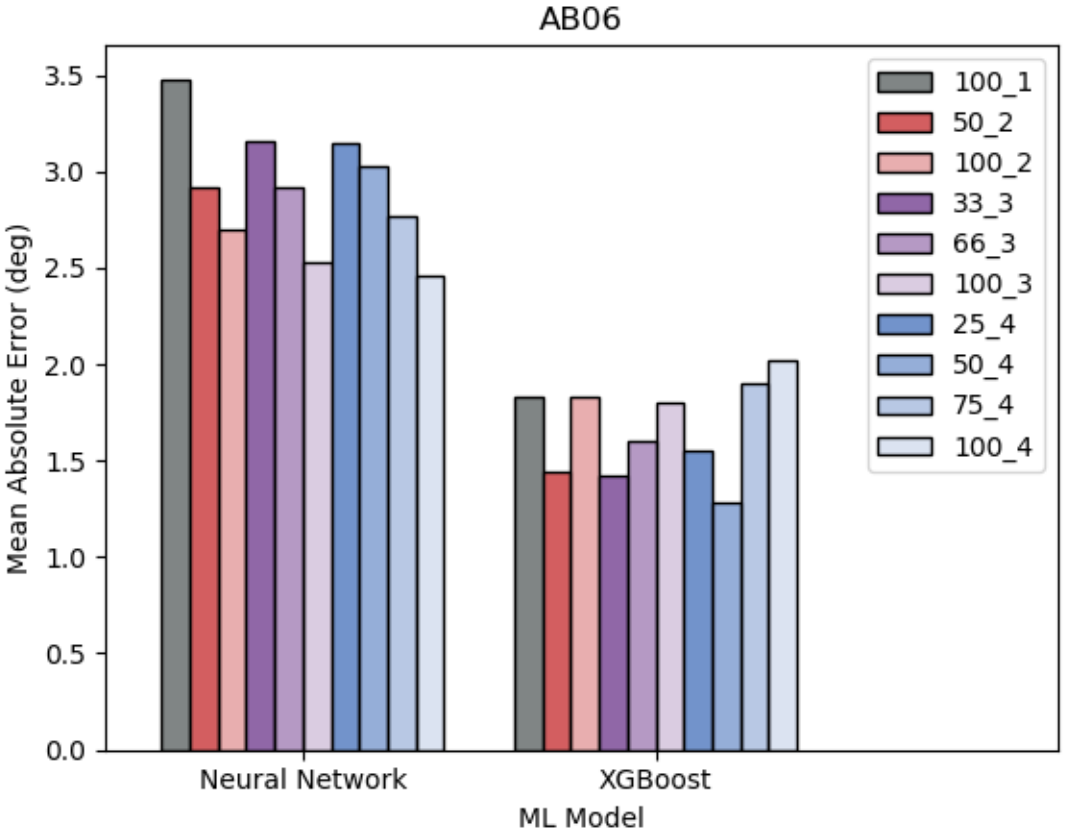


Figure 21: Comparison between machine learning algorithms on a user-independent case. Different models were trained on each gait phase across the 4 types of phase-dependency (total of 10 models for each phase conditions). This figure shows that our machine learning algorithm (XGBoost) was able to accurately estimate slope inclination angle and generalize across users even with varying speeds.

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

We used the inverse kinematics and dynamics from the software OpenSim to study the biomechanics of stairs ascent for N=7 subjects wearing the powered prosthesis and their personal passive prosthesis. Figure 22 and Figure 23 present the comparison of the prosthesis side and the sound side biomechanics, respectively. In both figures, the biomechanics of healthy individuals are displayed as a reference (AB).

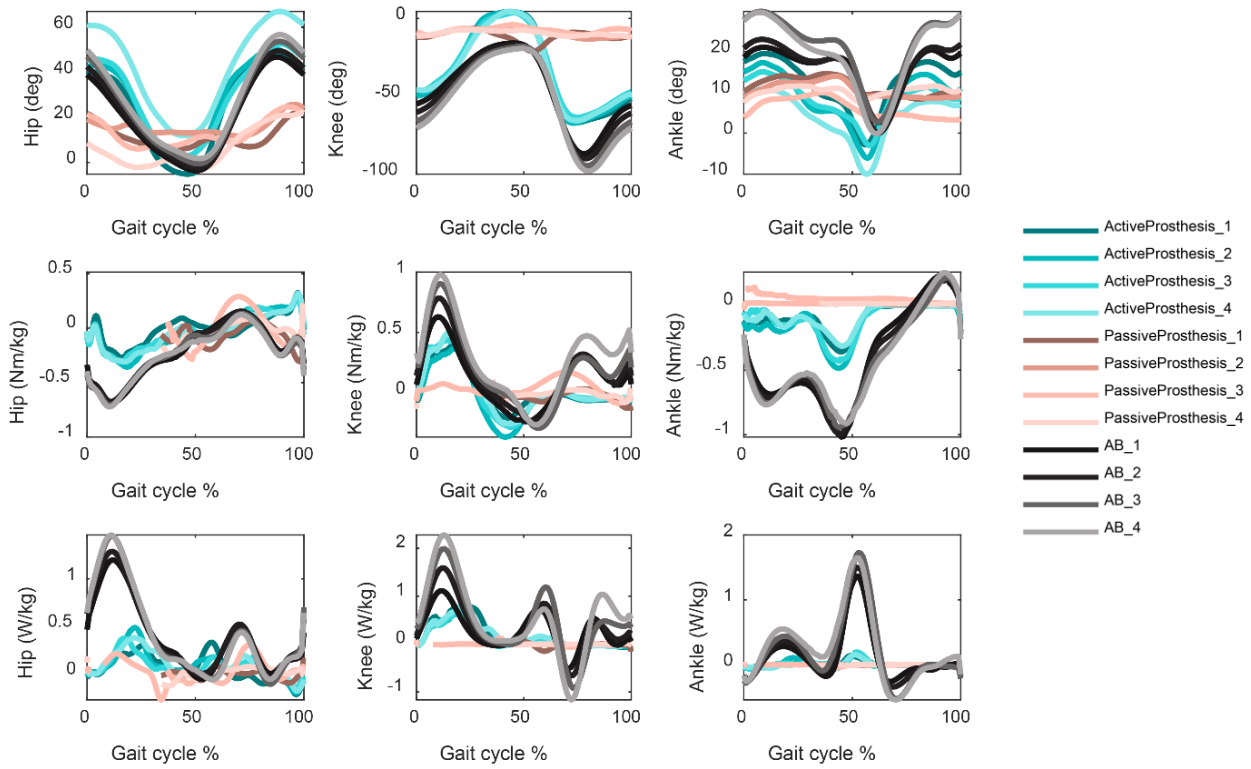


Figure 22: Amputated side biomechanics of stairs ascent at different heights raging from 4in-7in. Joint angle, moment and power delivery for individuals with amputation wearing an active prosthesis, a passive prosthesis, and as a reference, individuals without amputation (AB).

Kinematics of the prosthesis side show the significant difference of using an active prosthesis for the stair ascent task, with motion profiles that resemble the biological counterpart. The use of passive prosthesis limits the range of motion of the joints. In contrast, active prosthesis provides joint moments that share a similar profile with the biological. The kinematics of the sound side were relatively close to the biological reference. The joint moments for both knee and ankle exhibit an increase in magnitude in the case of passive prosthesis. For the active prosthesis, the energy contribution from the actuated joints aids in reduction the compensatory use of the sound side. Figure 24 shows qualitative results recorded from users when comparing their everyday prosthesis to our powered prosthetic device (see Appendix D for survey that was administered). It can be seen that the functional benefits of having positive power through an active device can help individuals ambulate better across different terrains.

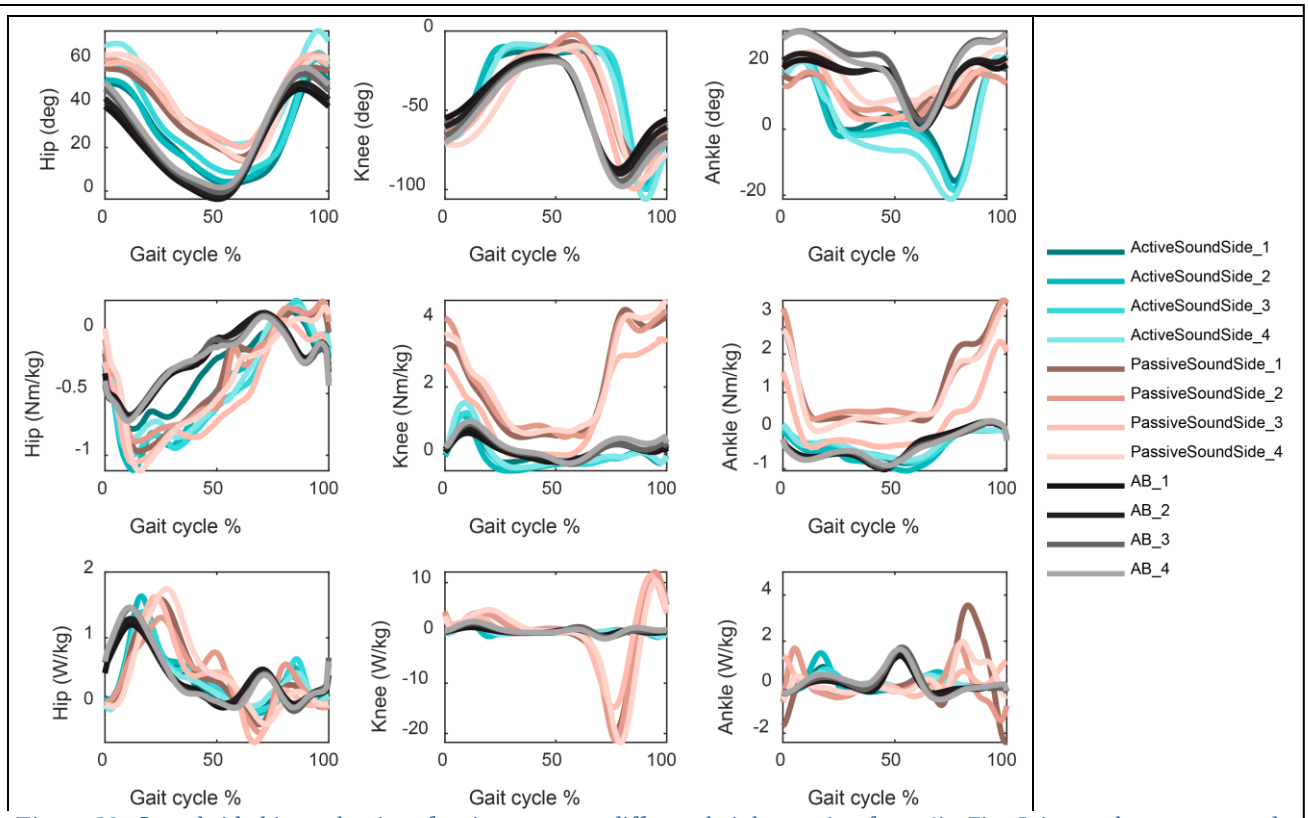


Figure 23: Sound side biomechanics of stairs ascent at different heights raging from 4in-7in. Joint angle, moment and power delivery for individuals with amputation wearing an active prosthesis, a passive prosthesis, and as a reference, individuals without amputation (AB).

PEQ Results

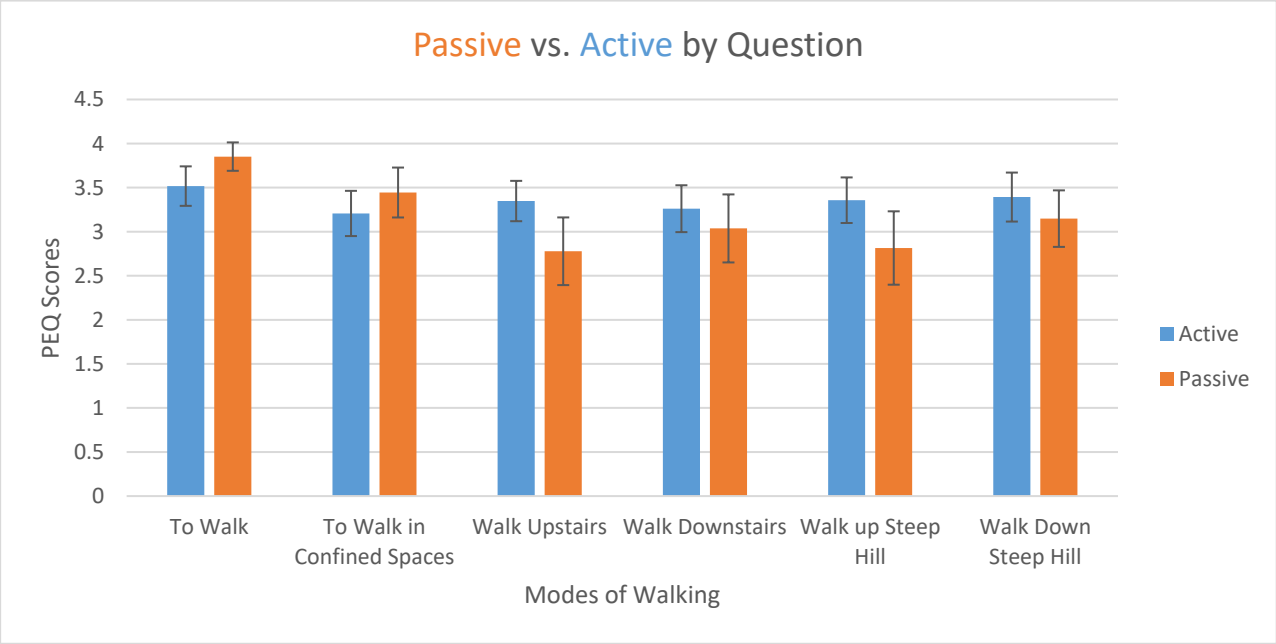


Figure 24: PEQ Results from survey conducted from different individuals over multiple sessions collected using the powered prosthesis compared to their conventional prosthesis.

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.

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. Another outreach was hosting a NSF summer camp where high school students learned how to make autonomous driving robots that utilized mechanical and biological signals. 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. We also were able to present our research to the MHSRS conference to a more technical audience on powered prosthetic technology.

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

1. We plan to finish modeling the OSL device in OpenSim to begin performing more in depth biomechanics analysis. As soon as this step is completed, we will begin performing our experiments with motion capture to do a better comparison of powered and passive devices.

2. We will continue performing experiments with the Open Source Leg to create user-independent pattern recognition systems that can enhance capabilities provided by a powered prosthesis. The goal will be to inform how to dynamically scale applied assistance to allow for smoother and more natural movements across different ambulation models. Further optimization of the user-independent system will be performed from prior experiments. This will help us refine our methods and translate them to the new leg.
3. We will begin performing trials of real-time machine learning algorithms integrated with our control system. We will begin with trying to ensure that a reasonable output can be generated from the machine learning estimators for both mode classification and continuous environmental 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 walking speed, inclination angle, and stair heights.
4. Begin pilot experiments were measures of metabolic cost and completion time will be recorded as the user performs ambulation circuits across the terrain park. As the user is doing these circuits, a key feature will be that the machine learning algorithm will automatically transition between modes depending on user intent.

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

No major issues. As noted in previous reports, we are behind schedule both due to additional modifications needed to make our prototype robust (Year 1 delays) and major lab renovations (Year 2 delays), but have made steady progress since then. We also got permission last year to build out a new, lighter weight, and more functional knee/ankle prosthesis that is much closer to a clinical system. We have completed the system but it was a significant development effort. We are working to transition our code and experiments to the new device. This has put some further delays as we want all of our future testing to be with the new and improved device which we believe will have better clinical outcomes. Budget wise, we have spent conservatively during downtimes in order to preserve funds for the human subject testing still to be done. Overall, our spending on the grant compared to the work accomplished is in very good shape. We believe we have made significant accomplishments and have also preserved funds to ensure the completion of the experiments by the end of the NCE year and would prefer to ask for a second NCE year to finish data analysis on the project if allowed to maximize the overall return on this project from a scientific perspective.

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 was accepted this year and will be provided as a supplement in a future report once it is in final electronic form. Our MHSRS 2019 abstract was presented as a poster at the MHSRS conference in August 2019 describing our machine learning strategies to improve prosthetic controllers (See Appendix C). Other seminar talks were given by Dr. Young at various institutions to discuss results generated using our powered prosthetic device.

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

Nothing to report

Other publications, conference papers, and presentations.

1) Our conference paper to the 45th Meeting of the American Academy of Orthotists & Prosthetists was accepted. 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. This conference paper discussed some of the initial biomechanical results with the powered leg compared to a passive leg. This work was presented in March 2019. (See Appendix A)

2) We submitted an abstract in February of 2019 to the Military Health System Research Symposium (MHSRS) conference and it was accepted in May 2019. The title of this abstract is: "Machine learning strategies for automatically determining ground slope and walking speed for individuals with amputation using a robotic knee/ankle prosthesis" The authors (in order) are: Trent Rankin, Krishan Bhakta, Jonathan Camargo-Leyva, Kinsey Herrin, Lee Childers, and Aaron Young (PI). Dr. Young presented a poster at the symposium in August 2019. (See Appendix B and C).

3) Our journal paper to the MHSRS Supplement, Military Medicine has been officially accepted. The title of the paper is "Impedance Control Strategies for Enhancing Sloped and Level Walking Capabilities for Individuals with Transfemoral Amputation Using a Powered Multi-Joint Prosthesis". The paper will be provided as a supplement in a future report once it is available in its final electronic form.

4) Dr. Young presented results of this work on numerous occasions throughout 2019 in seminar talks. These include talks to the Biomechanics group at the University of Omaha, to Shriner's hospital in South Carolina, the Dept. of Mechanical Engineering at Vanderbilt, and the department of mechanical engineering at the University of Alabama.

- **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 old 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. Furthermore, we have developed a new iteration of the leg that is lighter and more adaptable to the user. 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: *7*
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: *3*
Contribution to Project: *No change*

Name: *Krishan Bhakta*
Project Role: *Graduate Student*
Researcher Identifier:
Nearest person month worked: *39*
Contribution to Project: *No change*

Name: *Jonathan Camargo-Leyva*
Project Role: *Graduate Student*
Researcher Identifier:
Nearest person month worked: *39*
Contribution to Project: *No change*
Funding Support: *Fullbright Fellowship*

Name: *Jairo Maldonado-Contreras*
Project Role: *Graduate Student*
Researcher Identifier:
Nearest person month worked: *4*
Contribution to Project: *No change*

Name: *Trent Rankin*
Project Role: *Master's Student*
Researcher Identifier:
Nearest person month worked: *9*
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: *3*
Contribution to Project: *Helped to fit amputees to the powered prosthesis.*

Name: *Maximillian Spencer*
Project Role: *MSPO Student*
Researcher Identifier:
Nearest person month worked: *3*
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: *3*
Contribution to Project: *Help with biomechanics analysis with prosthesis*

Name: *Alanna Dyko*
Project Role: *Emory PT Student*
Researcher Identifier:
Nearest person month worked: *3*
Contribution to Project: *Help with biomechanics analysis with prosthesis*

Name: *Aiden Yoon*
Project Role: *Emory PT Student*
Researcher Identifier:
Nearest person month worked: *3*
Contribution to Project: *Help with biomechanics analysis with prosthesis*

Name: *Phillip Kellogg*
Project Role: *Emory PT Student*
Researcher Identifier:
Nearest person month worked: *3*
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*

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Contribution to Project: *No change*

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Contribution to Project: *No change*

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Project Role: *Undergraduate Researcher*
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Contribution to Project: *No change*

Name: *Noah Cho*
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Name: *Pratik Kunapuli*
Project Role: *Undergraduate Researcher*
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Name: *Stephen Mock*
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Name: *Ji Bok*
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Contribution to Project: *No change*

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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?

No change

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:

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

Appendix B: Military Health System Research Symposium (MHSRS 2019) Abstract

Appendix C: Military Health System Research Symposium (MHSRS 2019) Poster

Appendix D: Prosthetic Survey

Appendix A: 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]
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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.

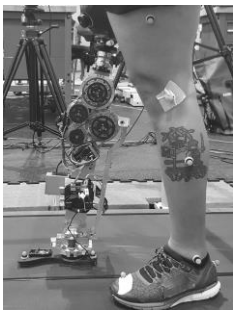
REFERENCES

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.

1.)



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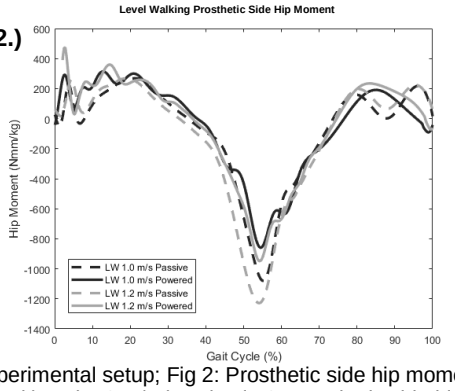

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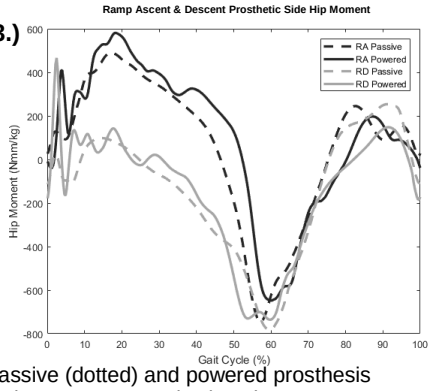


(Left to right): Fig 1: Powered prosthesis and experimental setup; Fig 2: Prosthetic side hip moment for the passive (dotted) and powered prosthesis (solid) during level ground walking at 1.0 m/s (black) and 1.2 m/s (grey); Fig 3: Prosthetic side hip moment during ramp ascent (RA) and ramp descent (RD)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

American Academy of Orthotists & Prosthetists
45th Academy Annual Meeting & Scientific Symposium
March 6-9, 2019

Appendix B: Military Health System Research Symposium (MHSRS 2019) Abstract

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

Authors: Trent Rankin, Krishan Bhakta, Jonathan Camargo-Leyva, Lee Childers, Kinsey Herrin, and Aaron Young

Date of Conference: August 19th – 22nd 2019

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 lower limb amputees to function at higher levels in their daily lives. Passive prostheses do not offer the personal assistance and mobility that many individuals with amputation need nor do they restore the active muscle power generation lost following an amputation. Powered prostheses have the potential to adapt to user intent and environment parameters to help increase functional mobility. One example of user intent is desired walking speed. Passive prosthesis users tend to walk with a reduced self-selected walking speed and are often constrained to a single or narrow range of functional walking speeds due to passive mechanics of the device, thus limiting the individual's rehab potential to functionally less than prior to the amputation. However, powered prostheses have the capability to adapt the assistance depending on desired speed to enable a faster self-selected walking speed and a larger functional range of speeds, thus restoring functional mobility to near pre-amputation level. Additionally, powered prostheses have the capability to adapt assistance depending on the ground slope of the walking surface. Many passive prosthesis users attempt to avoid significant grades altogether because their devices are not well tuned for walking on slopes. We are investigating strategies to automatically detect and adjust powered assistance depending on walking speed and ground slope. We present a new machine learning strategy that uses internal mechanical sensors on a powered knee/ankle prosthesis to determine a wide range of ground slopes and walking speeds based on human subject experiments of individuals with transfemoral amputation using the device.

Methods:
Powered Knee/Ankle Prosthesis: The device used in all experiments was a powered prosthetic leg, consisting of two brushless DC motors acting as the knee and ankle joints, embedded electronics to enact the state machine for variable impedance control across locomotion modes, and an on-device battery for power distribution. Data collection occurred on the device with six mechanical sensors: two encoders residing on the motors to collect joint position and velocity, one load cell sensor for collecting the force and torque values at the ankle of the leg, and three inertial measurement units (IMUs) to provide acceleration and rotational velocity information at the foot and shank of the device, and the residual thigh of the subject.

Experimental Protocol: Before all experiments, the device was fitted and dynamically aligned by a certified prosthetist after the patient reviewed and gave informed consent to an IRB approved protocol. Control parameters were then tuned until subjects felt comfortable walking overground. The protocol consisted of walking on a treadmill with variable speeds and walking on a ramp with different inclinations. In the treadmill experiments, the subjects (N=4) walked on a treadmill for 60 seconds for each static speed tested. The speed ranged from 0.5 m/s to the maximum user preferred speed (0.9 to 1.1 m/s) in increments of 0.05m/s. In the ramp experiments, the subjects (N=4) performed 15 slope trials to collect three circuits at five slopes: 5.2, 7.8, 9.1, 11.0 and 12.4 degrees. A circuit consisted of 18 steps across a terrain park with a 16-foot ramp. The subject began on level ground, walked up the ramp, turned around and walked down the ramp back to level ground to include all relevant transitions. Using the output of the

finite state machine, precise labeling was applied to the data to indicate the true mode at every time step.

Offline Slope and Speed Estimation: To develop continuous machine learning estimators, data was processed and segmented by the phases dictated by the finite state machine: early stance, late stance, swing flexion and swing extension; this determined which phase would produce the lowest estimation error. Data was represented by six time-domain features (mean, standard deviation, minimum, maximum, starting and ending value) resulting in 168 total features. Two strategies to improve prediction accuracy were sweeping the window of time over which these features were calculated between 50, 100, 250 and 500 ms, and sensor selection to determine their contribution to the performance of the estimation. The two encoders were included by default, whilst data from the other four sensors was added sequentially to determine which sensor was the most beneficial. The process was repeated until a rank of the important sensors was established. Neural network models were selected as the machine learning estimators due to their inherent ability of being able to update the model based off of new examples of data. Various hyperparameters (number of neurons, learning rate, activation function, etc.) were optimized to maximize the prediction accuracy. Performance was evaluated using the mean absolute error between the estimated and the true output, as an average across subjects with "leave one out" cross-validation across trials.

Results and Discussion:

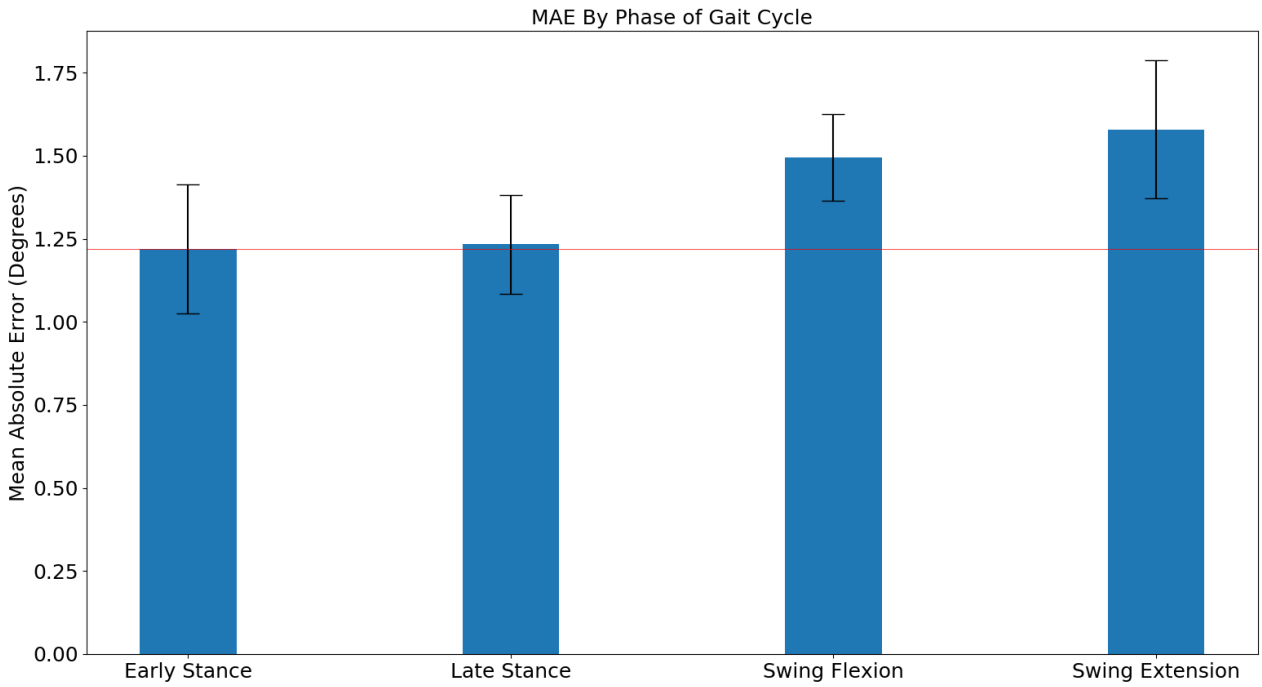
All numbers reported are the average mean absolute error scores between the true labels and the output estimations from the trained regression models. For walking speed, the machine learning error performance as a function of gait phase were 0.025 ± 0.026, 0.029 ± 0.029, 0.040± 0.038, and 0.042 ± 0.040 m/s for early stance, late stance, swing flexion and swing extension, respectively. For the ramp experiments, the machine learning error performance as a function of gait phase were 1.22 ± 0.19, 1.23 ± 0.14, 1.50 ± 0.13 and 1.58 ± 0.21 degrees for early stance, late stance, swing flexion and swing extension respectively. Further, varying the feature generation window size resulted in scores of 1.31 ± 0.17, 1.27 ± 0.18, 1.22 ± 0.19 and 1.26 ± 0.21 degrees for 50, 100, 250 and 500ms. According to these results, slope prediction will see the best performance if estimated during early stance using the past 250 ms of data. Using this method and monitoring the error with respect to time after mode transitions, a score of 1.25 ± 0.21 degrees was able to be achieved as soon as 320 ms after heel strike. The results of the forward sensor selection search found that the load cell was the most valuable sensor to add to the encoders followed by in order by the thigh IMU, then foot IMU, and lastly the shank IMU. The encoders only had mean error of 2.13 ± 0.25 degrees, adding the load cell reduced this to 1.55 ± 0.22 degrees, and 1.34 ± 0.20, 1.24 ± 0.20, and 1.22 ± 0.19 degrees for adding each IMU in the selected order. This shows that all sensors were necessary for reducing the estimation error, though the absolute reduction decreased with each sensor added.

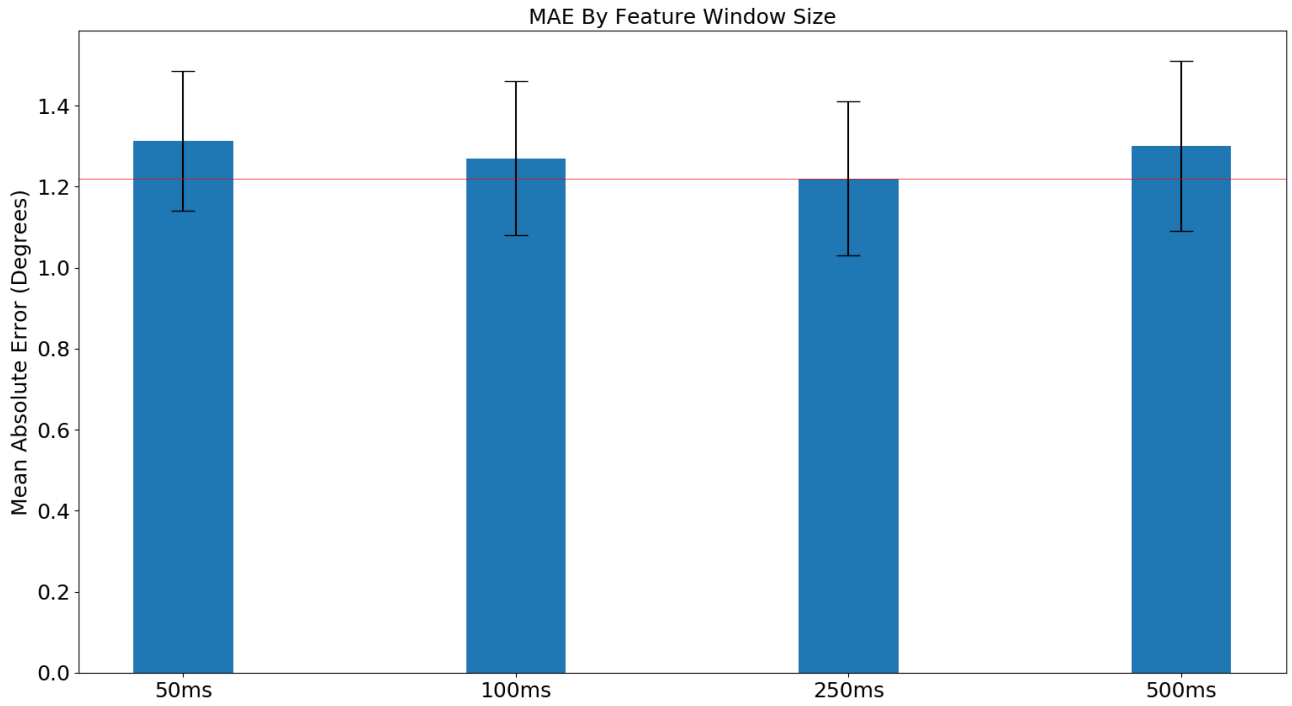
Conclusions:

The primary finding of this study was to demonstrate a machine learning strategy capable of accurate walking speed and ground slope estimation. We achieved this goal by developing a system that estimates walking speed with errors below 0.05 m/s and ground slope below 1.25 degrees. We believe these machine learning errors represent a system capable of enabling better performance using a powered prosthesis by modulating assistance based on the user's desired

walking speed and the amount of incline/decline of the surface. This is an important problem for helping to translate powered prostheses clinically for use in the community. Our results suggest critical features of the machine learner such as best practices as to when to estimate these parameters during the gait cycle and the potential value added of common sensors that could be embedded in a mechanical prosthesis.

Here are the reference figures for the slope estimation numbers:




MAE By Feature Window Size
Mean Absolute Error (Degrees)
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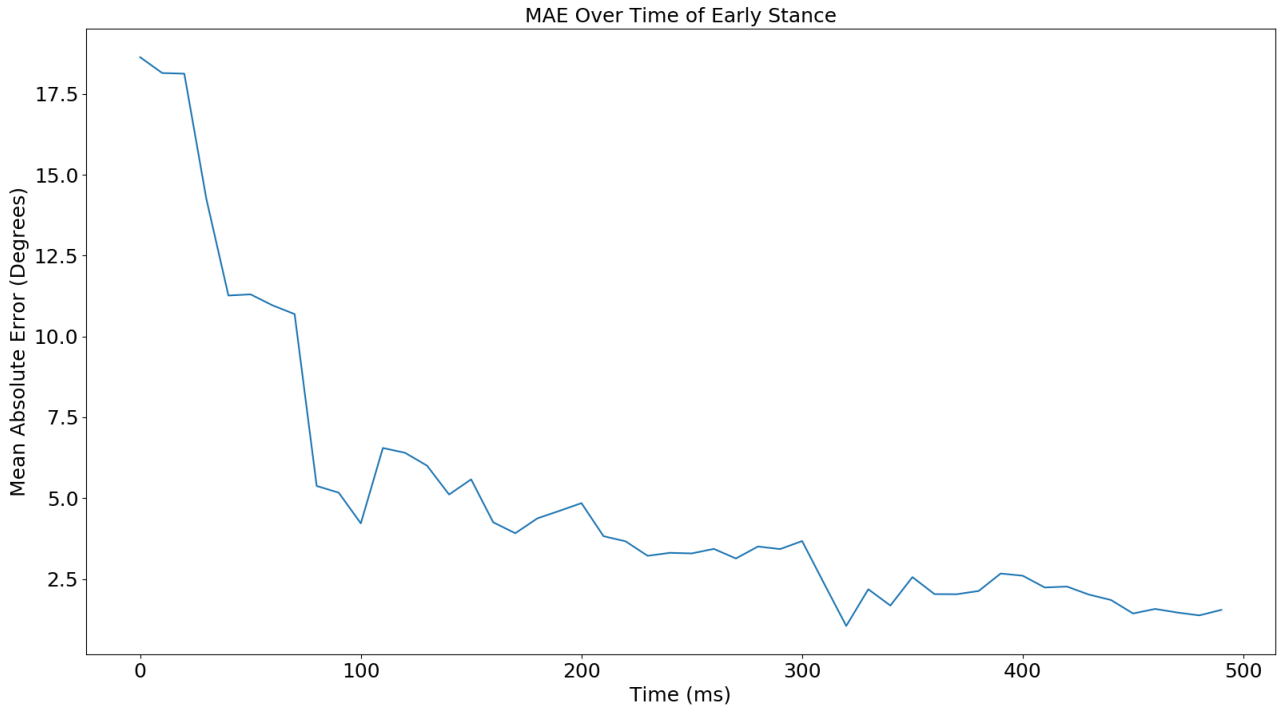
0.2
0.4
0.6
0.8
1.0
1.2
1.4
50ms
100ms
250ms
500ms


MAE Over Time of Early Stance
Mean Absolute Error (Degrees)
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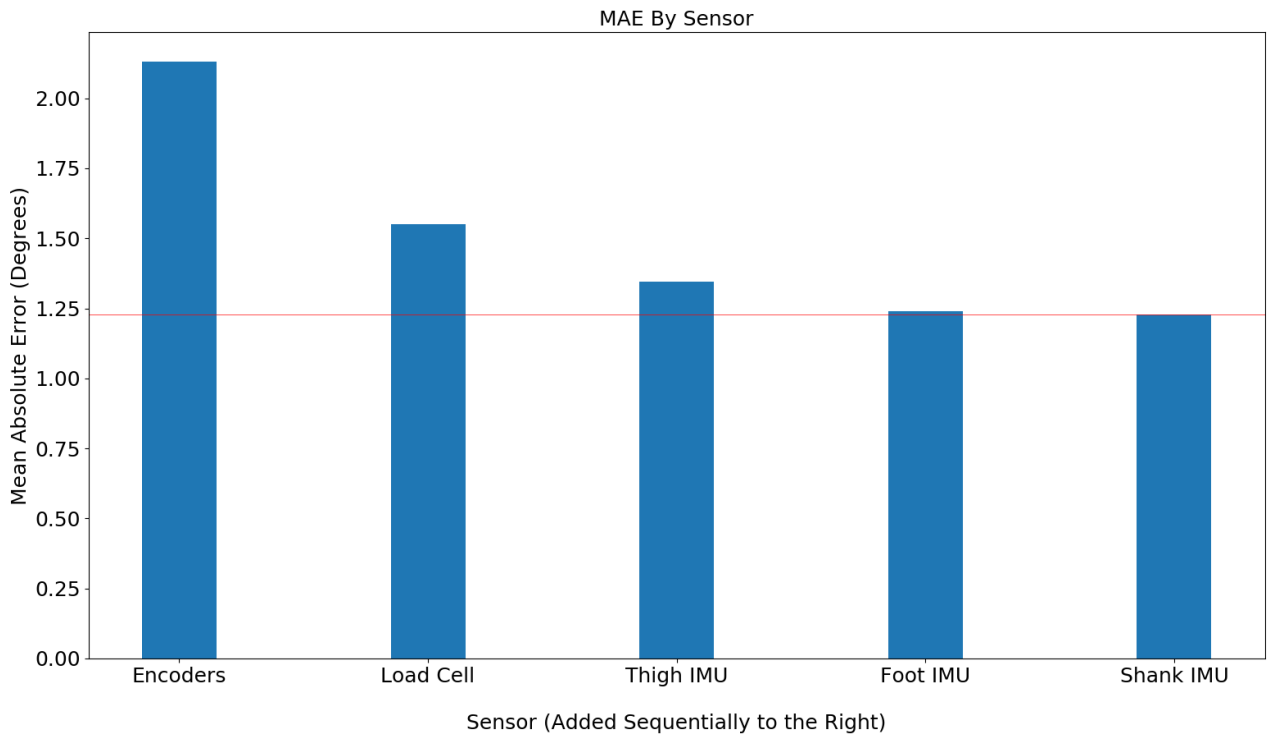
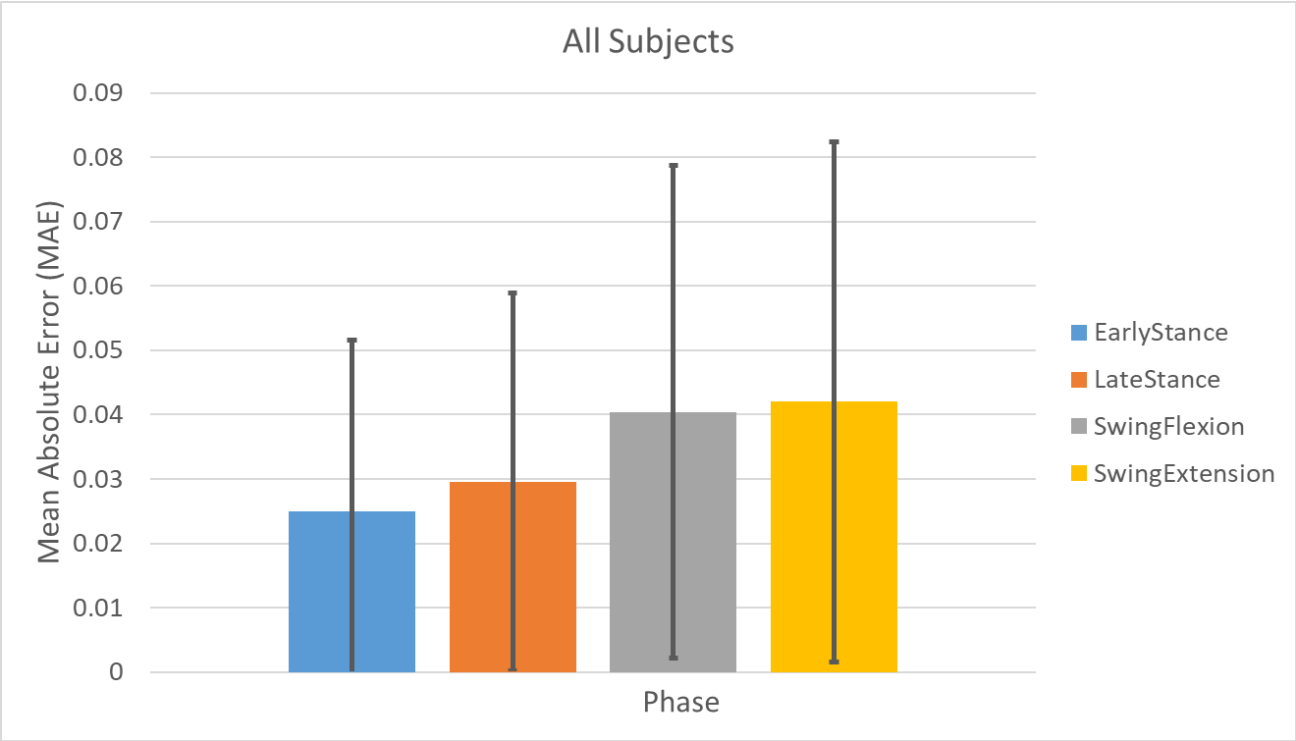
7.5
10.0
12.5
15.0
17.5
0
100
200
300
400
500
Time (ms)



Here are the reference figures for walking speed estimation:



Appendix C: Military Health System Research Symposium (MHSRS 2019) Poster

Title: Machine Learning Strategies for Automatically Determining Environmental Variables for Individuals with Amputation using a Powered Prosthesis

Authors: Trent Rankin, Krishan Bhakta, Jonathan Camargo-Leyva, Lee Childers, Kinsey Herrin, and Aaron Young

Date of Conference: August 19th – 22nd 2019

Location of Conference: Kissimmee, Florida

Machine Learning Strategies for Automatically Determining Environmental Variables for Individuals with Amputation using a Powered Prosthesis

Trent Rankin[1], Krishan Bhakta[2], Jonathan Camargo[2,3], Lee Childers[4,5], Kinsey Herrin[6], Aaron Young[2,3]

[1]School of Electrical and Computer Engineering, College of Engineering, Georgia Institute of Technology, Atlanta, GA USA, [2]Woodruff School of Mechanical Engineering, College of Engineering, Georgia Institute of Technology, Atlanta, GA USA, [3]Institute for Robotics and Intelligent Machines, Georgia Institute of Technology, Atlanta, GA USA, [4]Extremity Trauma and Amputation Center of Excellence, JBSA Ft. Sam Houston, TX, USA, [5]Center for the Intrepid, Department of Rehabilitation Medicine, Brooke Army Medical Center, JBSA Ft. Sam Houston, TX, USA, [6]School of Biological Sciences, College of Sciences, Georgia Institute of Technology, Atlanta, GA USA

Introduction

The number of individuals suffering with lower-limb amputations is steadily increasing over the next couple of decades[1]

Disadvantages of using current passive prostheses:

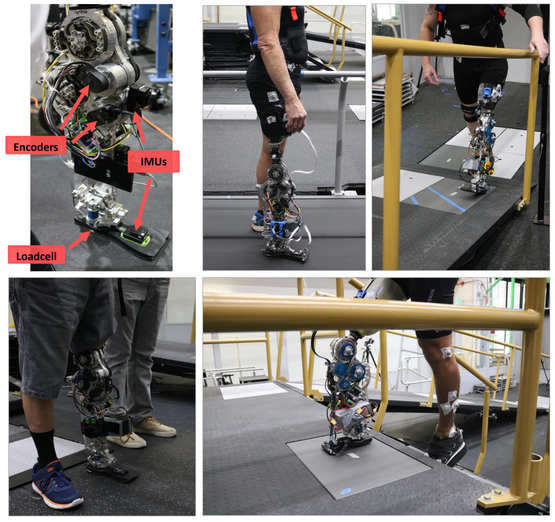
- Asymmetric gait patterns[2,3]
- Increased energetic demands[2,3]
- Difficulty adapting to slopes & stairs
- Non-intuitive control requiring the use of unnatural movements from the user to transition between walking modes

Powered prostheses coupled with intelligent machine learning strategies may help overcome these issues

Research Question: *How do we accurately determine user state in order to adapt control for variable speed and grade?*

Hypothesis: Sensor fusion with machine learning can enable user state estimation with greater accuracy than analogue sensor measurements.

Powered Knee & Ankle Prosthetic Device

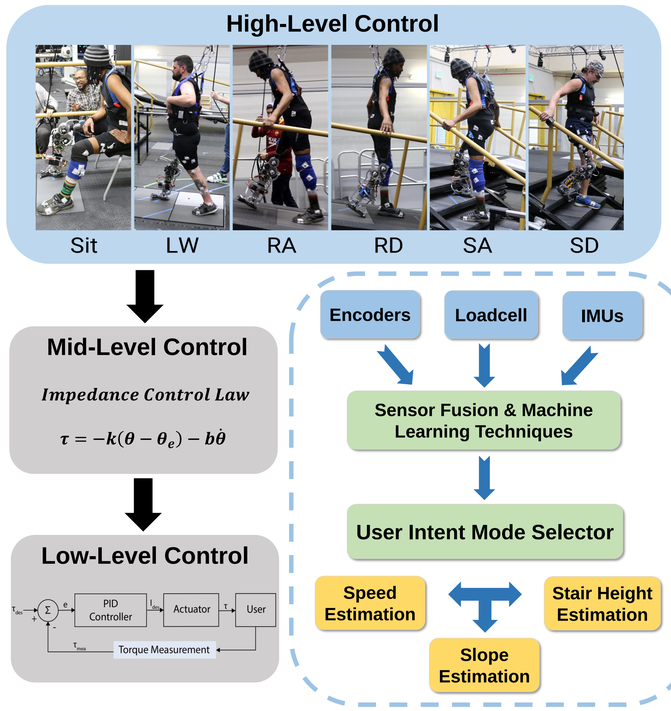


Close up of the powered prosthesis embedded with different mechanical sensors (top left) and individuals wearing the powered prosthesis with embedded electronics and walking in different ambulation modes.

Experimental Approach

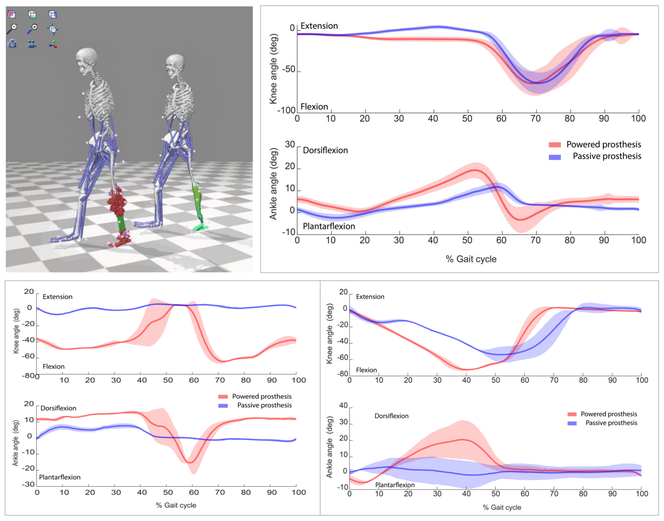
- Four persons with transfemoral amputation were asked to perform two experimental protocols; variable speed treadmill walking and slope ambulation circuits
- Speed ranged from 0.5 m/s to maximum preferred walking speed in increments of 0.05 m/s
- 15 slope trials were performed to collect three circuits at five different inclination angles: 5.2, 7.8, 9.1, 11.0, and 12.4 degrees.

Control Methodology



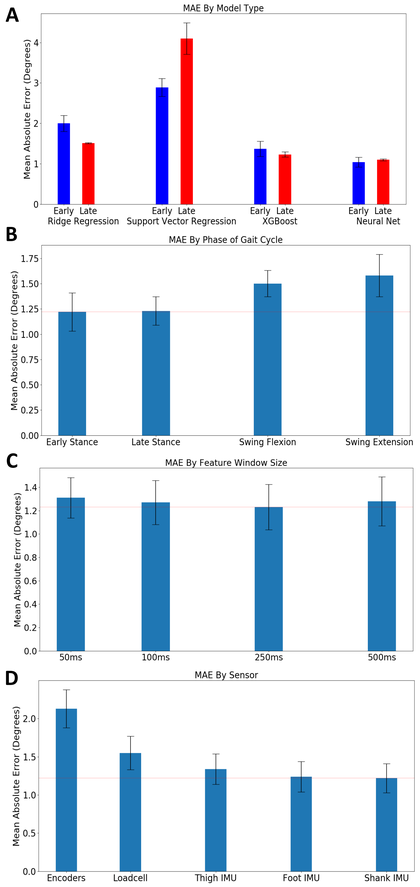
Control Architecture: High-level controller estimates user states (i.e. mode selection followed by environment estimation), mid-level controller uses dynamic equations to prescribe joint torques, and low-level controller matches robotic torque to commanded torque.

Preliminary Biomechanics Results

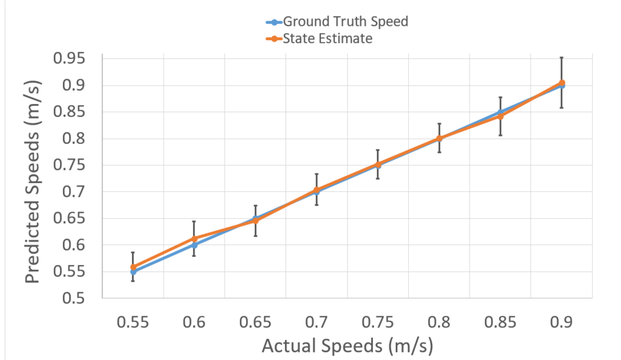


OpenSim model generated in order to perform a biomechanical analysis between prostheses (top left). Powered versus passive joint kinematics across 3 different ambulation modes: level-walking (top right), slope-ascent (bottom left), and slope-descent (bottom right). Results show that powered prostheses are better suited in adapting to different terrain.

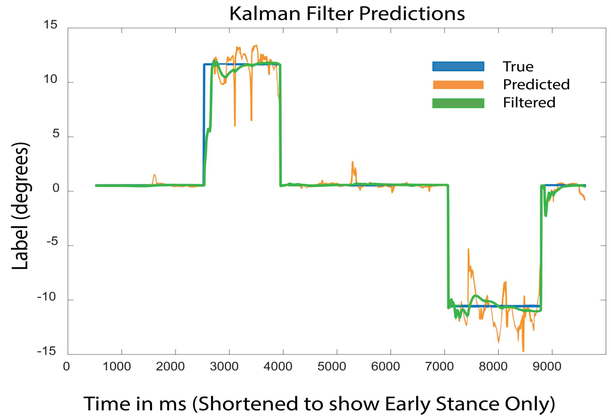
Machine Learning Results



Mean absolute error (MAE) for A) Model selection of different machine learning algorithms (neural networks show best performance), B) Individual models trained for each phase, C) Window size sweep for EarlyStance, and D) sensor selection to determine which sensors are most useful based on leave-one-out.



Comparison plot of predicted speed versus actual speed across walking speeds using a remove-one-speed validation. Our optimized machine learning algorithm (neural network) is able to generate accurate state estimates of unknown walking speeds under our trained range of speeds. Average MAE is 0.0352 (N=4).



Comparison of raw prediction and Kalman filtered prediction versus ground truth of inclination angle in a ramp circuit in early stance.

Conclusions & Future Implications

- Primary findings demonstrate that machine learning strategies are capable of accurately estimating environmental variables (i.e. walking speed, slopes, and stair heights)
- This is useful step in translating this technology to clinical settings, where the prostheses can modulate assistance based on users' needs.

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[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] L. Nolan and A. Lees, "The functional demands on the intact limb during walking for active transfemoral and transtibial amputees," *Prosthet. Orthot. Int.*, vol. 24, no. 2, pp. 117–125, Aug. 2000.

[3] D. C. Morgenroth, M. Roland, A. L. Pruziner, and J. M. Czerniecki, "Transfemoral amputee intact limb loading and compensatory gait mechanics during down slope ambulation and the effect of prosthetic knee mechanisms," *Clin. Biomech.*, vol. 55, pp. 65–72, Jun. 2018.

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- EPIC Lab VIP Prosthetics & Sensor Fusion Team

Sponsors

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Appendix D: 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	☐	☐	☐	☐	☐