

AWARD NUMBER: W81XWH-17-1-0031

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

PRINCIPAL INVESTIGATOR: Aaron Young

RECIPIENT: Georgia Institute of Technology

REPORT DATE: February 2021

TYPE OF REPORT: Annual

PREPARED FOR: U.S. Army Medical Research and Materiel Command
Fort Detrick, Maryland 21702-5012

DISTRIBUTION STATEMENT: Approved for Public Release; Distribution Unlimited

The views, opinions and/or findings contained in this report are those of the author(s) and should not be construed as an official Department of the Army position, policy or decision unless so designated by other documentation.

REPORT DOCUMENTATION PAGE				Form Approved OMB No. 0704-0188	
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing this collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden to Department of Defense, Washington Headquarters Services, Directorate for Information Operations and Reports (0704-0188), 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to any penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number. PLEASE DO NOT RETURN YOUR FORM TO THE ABOVE ADDRESS.					
1. REPORT DATE FEBRUARY 2021		2. REPORT TYPE Annual		3. DATES COVERED 15JAN2020 - 14JAN2021	
4. TITLE AND SUBTITLE User-Independent Intent Recognition on a Powered Transfemoral Prosthesis				5a. CONTRACT NUMBER	
				5b. GRANT NUMBER W81XWH-17-1-0031	
				5c. PROGRAM ELEMENT NUMBER	
6. AUTHOR(S) Aaron Young Krishan Bhakta Jairo Maldonado E-Mail: aaron.young@me.gatech.edu				5d. PROJECT NUMBER	
				5e. TASK NUMBER	
				5f. WORK UNIT NUMBER	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Georgia Institute of Technology 813 Ferst Dr. NW Rm. 433; Atlanta GA 30332				8. PERFORMING ORGANIZATION REPORT	
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) U.S. Army Medical Research and Materiel Command Fort Detrick, Maryland 21702-5012				10. SPONSOR/MONITOR'S ACRONYM(S)	
				11. SPONSOR/MONITOR'S REPORT NUMBER(S)	
12. DISTRIBUTION / AVAILABILITY STATEMENT Approved for Public Release; Distribution Unlimited					
13. SUPPLEMENTARY NOTES					
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					
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT Unclassified	18. NUMBER OF PAGES 44	19a. NAME OF RESPONSIBLE PERSON USAMRMC
a. REPORT Unclassified	b. ABSTRACT Unclassified	c. THIS PAGE Unclassified			19b. TELEPHONE NUMBER (include area code)

TABLE OF CONTENTS

	<u>Page No.</u>
1. Introduction.....	4
2. Keywords.....	4
3. Accomplishments.....	5
4. Impact.....	32
5. Changes/Problems.....	33
6. Products.....	34
7. Participants & Other Collaborating Organizations.....	36
8. Special Reporting Requirements.....	44
9. Appendices.....	44

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 – 95% 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 – 10% 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 – 80% 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

The main hardware developments that has been done in the last quarter is to add a foot shell and shoe to reduce impact when ambulating in the terrain park allowing for smoother powered assistance. One of the main goals for this quarter was to implement a real time system that can automatically transition between walking modes (i.e. a machine learning mode classifier). Tests were done with individuals to train a simple mode when ambulating a stair circuit and we were successful in having the machine learning algorithm automatically transition between modes with manual triggers (See Major Task 4). Furthermore, ongoing analysis of the data from the old leg has enabled us to understand the bilateral biomechanics of a user when ambulating up and down a staircase (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 slope estimation and stair height estimation (See Major Task 4).

A manuscript has also been submitted to the IEEE Robotics and Automation Letters (RA-L) titled “Machine Learning Model Comparisons of User Independent and Dependent Intent Recognition System for Powered Prostheses”. This paper highlights our efforts in investigation subject independent mode classifiers.

Major Task 4: System Implementation

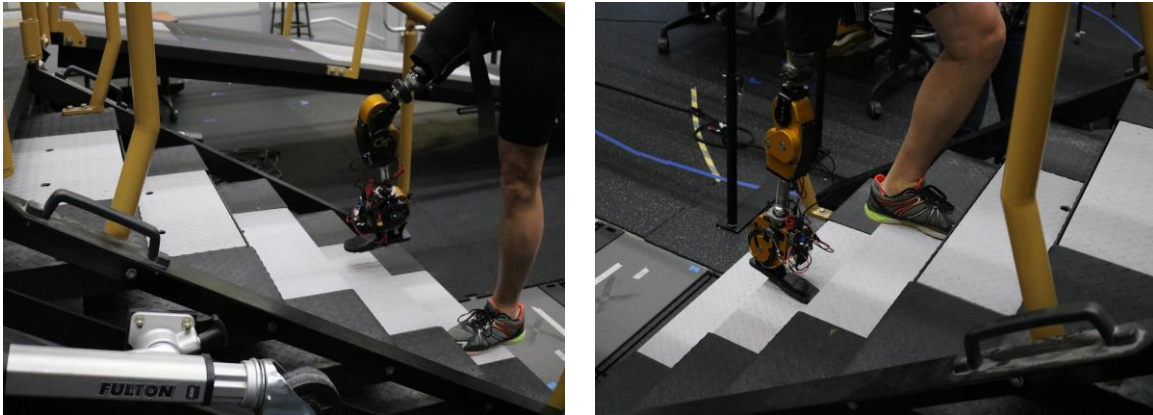


Figure 1: Individual with transfemoral amputation wearing the OSL while performing stair ambulation circuits. These images are from when the user was walking with the real-time system embedded on the onboard microprocessor.

By using embedded sensors on the OSL, we have created a custom control infrastructure for real time prediction/estimation. A focus of this quarter was to ensure that an individual walking on the powered prosthesis would be able to ambulate the same with and without the use of manual triggers (i.e. real time). From our last quarter, we had tested an offline paradigm to ensure a prediction of 50 Hz. We were then able to test in real time where an individual completed 12-15 stair circuits, a machine learning model was trained offline, and then embedded on the onboard microprocessor. The user was able to successfully ambulate the staircase with no external input from the researcher to transition between modes. This is promising as we continue to create and develop a real time user-independent system that can generalize across users. Future work will look at creating a tiered machine learning controller that can first predict walking modes followed by an environment estimator (i.e. stair height estimation and slope estimation).

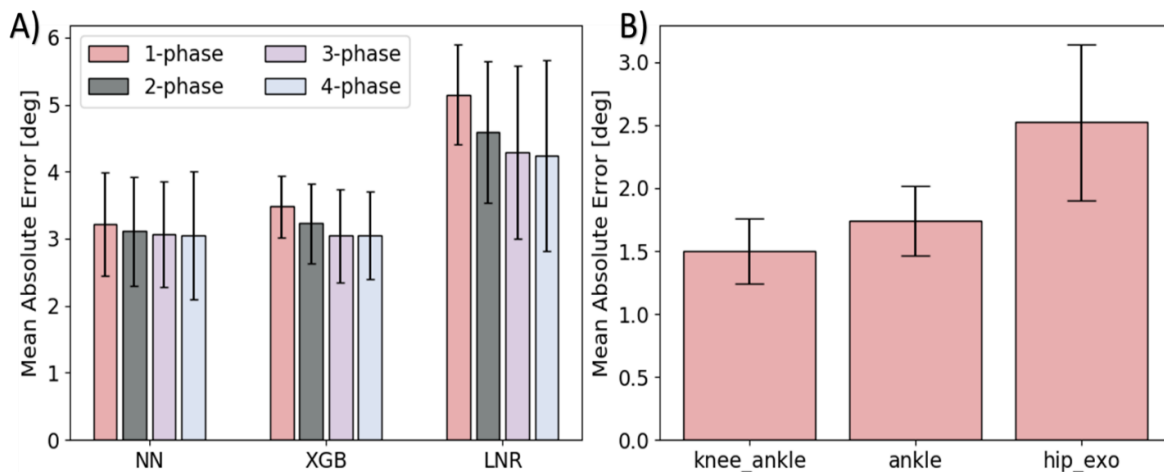


Figure 2: A) User independent model comparison for slope estimation across different phases to understand best gait locations to run a prediction/estimation. XGBoost has been the most useful algorithm in achieving a repeatable estimation with relatively low variance. B) Different sensor suites have been analyzed to understand how wearable sensors affect the overall error of estimating environmental variables.

As more powered prostheses and exoskeletons enter real-world settings, it is important to adapt assistance profiles in dynamic environments using slope level information. This analysis is expected to provide robust slope estimation methods for subsets of sensors found in ankle prostheses, knee-ankle prostheses, and hip exoskeletons. Analyses across different normalization methods, sliding window sizes, gait phases, and ML models were conducted to minimize slope estimation errors. Figure 2A shows that Feed-Forward Neural Network and XGBoost models similarly outperformed Linear Regression models across each gait phase, for the knee-ankle prosthesis sensor suite. We decided to continue our analyses with the XGBoost model due to its lower variances and the 1-phase gait cycle due to its simplicity. With the optimal window size of 500 ms, static trial average MAE errors of $1.500 \pm 0.258^\circ$, $1.739 \pm 0.276^\circ$, and $2.522 \pm 0.618^\circ$ were achieved for the knee-ankle, ankle, and hip-exoskeleton sensor suites, respectively (Figure 2B). Future analyses will test the performance of the proposed ML architectures on dynamic trials, identify a reduced feature space for each sensor suite, and include a Kalman filter to further reduce errors.

Using data collected from the old leg our findings were submitted to RA-L. With the challenge in creating smart robotic prosthesis for the lower limb, machine learning based pattern recognition techniques have been shown to classify the ambulation mode in powered prostheses from mechanical sensors and neuromuscular signals, demonstrating the potential application in the control of the ambulation mode of prosthetic legs. However, most of the results in literature have focus on the evaluation of methods that are heavily subject dependent with limited evaluation of models that can generalize the intent recognition across different individuals. Furthermore, most of the studies limit to the evaluation to a fixed terrain that is individual stair height and ramp inclination. In this manuscript we presented our investigation of the use of the XGBoost algorithm for developing a subject independent model. We evaluated the performance of XGBoost across different stair heights and inclination angles. Our findings suggest that XGBoost offers a potential benefit for both subject independent and subject dependent algorithms outperforming the traditional LDA. We observed that our model can predict the ambulation mode irrespective of the terrain characteristics that is stair height and ramp inclination with comparable results to the state-of-the art.

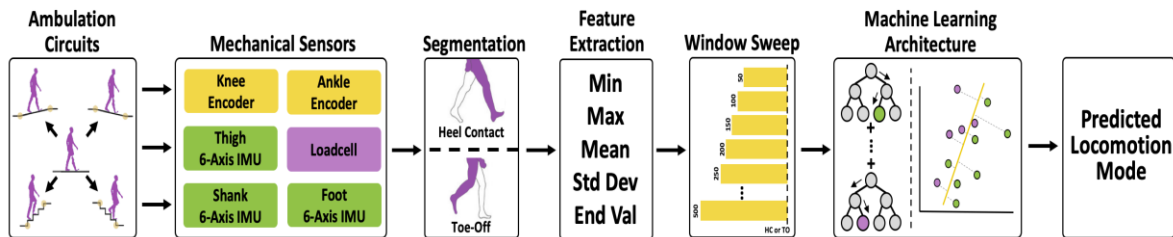


Figure 3: The machine learning workflow used to predict user locomotion mode is shown. Users were asked to perform ambulation circuits which involved walking in 5 locomotion modes - LW, RA, RD, SA, and SD. Features were then passed through each machine learning algorithm (LDA, QDA, and XGBoost) to predict locomotion mode. XGBoost had to undergo an extra step of hyper-parameter tuning where learning rate, maximum tree depth, regularization term, and minimum gain were swept. After an optimized set of parameters were chosen, models were trained for our 6 different case studies to predict locomotion mode.

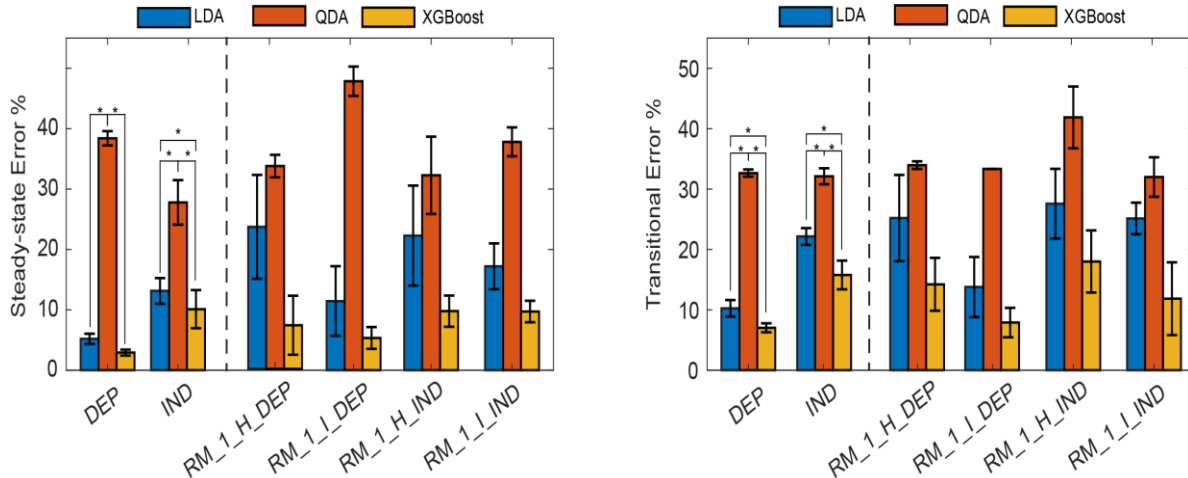


Figure 4: Three different models (LDA/QDA/XGBoost) were compared for the classification of ambulation mode in ramps, stairs and level-ground, resulting in XGBoost outperforming other models. The y-axis shows the performance metric, consisting of the error in classification during steady state walking within a mode and the error of transitioning between modes. The x-axis show the six conditions of evaluation: subject dependent i.e. training and testing on the same subject, subject independent i.e. training on all subjects but the testing subject, and remove-1 condition for the stair height and ramp inclination for both dependent and independent. Error bars represent standard error of the mean. Noted with * is the significant difference ($p < 0.05$).

In tandem, we have also been working on creating continuous regressors for estimating environmental variables. Specifically, Figure 5 shows results for the stair height estimator using the XGBoost algorithm. When computing the error across all 4 presets/heights (4 – 7 in) the lowest error in the dependent (DEP) case was in the SASD_HC conditions with an error of 2.065 ± 0.667 cm. This condition entailed data used in stair ascent and descent segmented at heel contact. In the independent (IND) case, the lowest error was 2.245 ± 0.473 cm found in the SA_TO. This condition included data from only stair ascent segmented at toe off. One good characteristic about regressors is their ability to interpolate between values which can be seen in the average values for the middle presets (5 & 6 in). The lowest error found in the DEP case was 1.249 ± 0.247 cm which occurred in SA_TO and in the IND case was 1.412 ± 0.197 cm which occurred in the SASD_HC condition. These results are promising as they show that we can achieve decent estimated results for stair heights. Next steps will be to do a thorough machine learning analysis and utilize a kalman filter to enhance results.

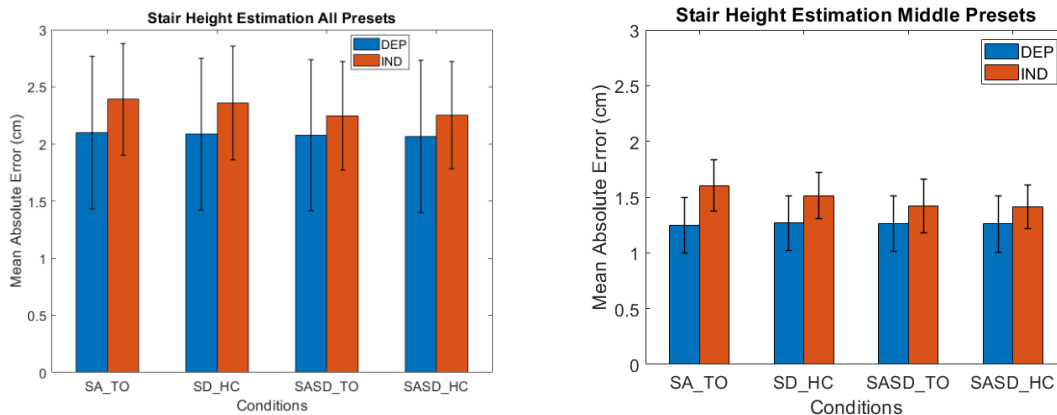


Figure 5: Stair height estimation using XGBoost. Mean absolute error from the stair height estimator shown across both dependent (DEP) and independent (IND) cases. It can be seen that these results show promise in being able to provide accurate estimation that can be embedded into our prosthetic device.

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

To further enhance our biomechanical analysis between powered and passive prostheses, we also developed the Open Source Leg model in OpenSim (Figure 6). 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. In the upcoming quarters, we will validate to ensure that our model is able to capture and return sound biomechanics as users are ambulating different modes.

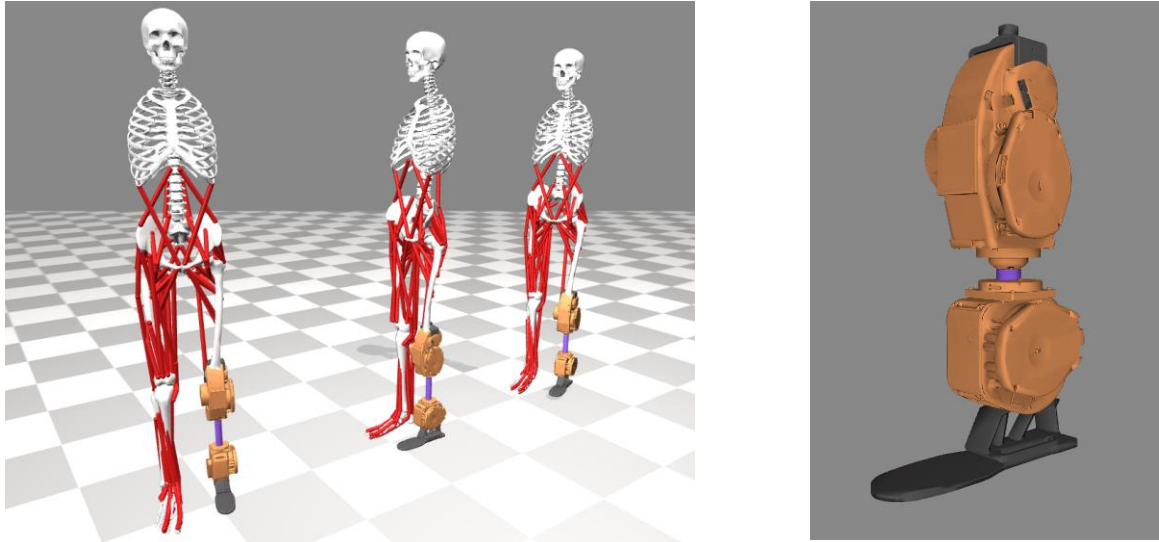


Figure 6: OpenSim model of the OSL created in order to better perform biomechanical analysis of calculating kinematics and kinetics using forceplates and motion capture.

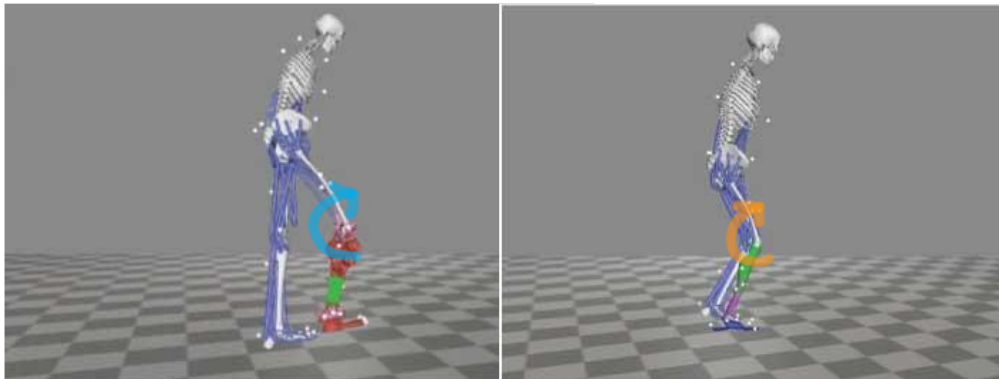


Figure 7: Stair ascent task with active prosthesis and passive prosthesis. The torque at the knee level is the target for modulation and it is illustrated by a moment arrow.

Using the powered prosthesis, we can enable the contribution of positive work, with the potential of providing biomechanics outcomes that better resemble such of a healthy individual. Using the information from kinematics and kinetics patterns of locomotion of able-bodied subjects we can generate adaptations of our baseline impedance control to emulate the modulation of the joint torque to different conditions of terrain context. We studied the stair ascent task as an example of the process of implementing contextual modulation of the impedance control. Figure 8 presents the torque profile of during a stair ascent task for N=22 healthy subjects in comparison to the powered prosthesis (N=7) and a passive prosthesis (N=7).

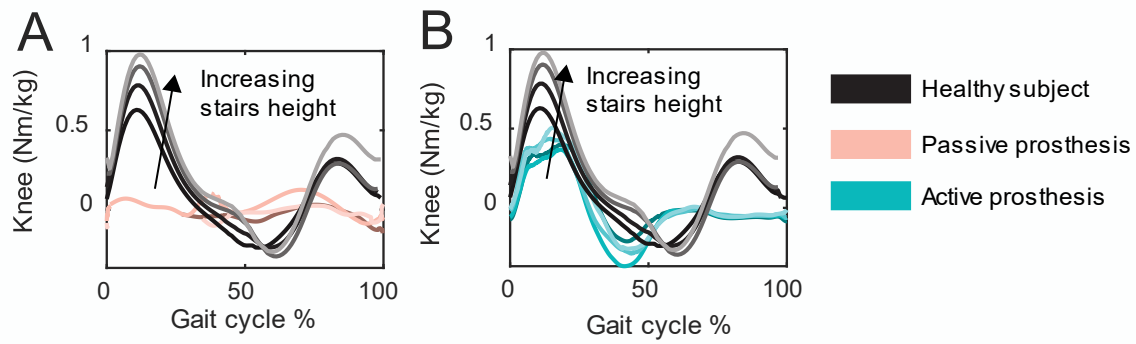


Figure 8: Knee torque during stair ascent task for healthy subjects and individuals with transfemoral amputation using a passive prosthesis and an active prosthesis. Healthy subjects exhibit modulation of torque for a change in condition of the stair height.

It is observed that during the stance phase, the healthy subjects produce a peak of extension torque at the knee that consistently increases as the stair's height increase, making an adaptation to the more challenging task. For the case of a passive prosthesis (Figure 8A), there is no actuator to provide considerable torque at the joint level. In comparison, an active prosthesis is able to generate a nominal torque during stance phase (Figure 8B). However, as the baseline impedance controller does not adapt to the terrain condition, the torque at the knee does not present the modulatory pattern of the healthy individuals. For this, we proposed the implantation of a modulation factor for the stiffness of the knee. This factor generates the adaptation of the joint torque to the terrain context, in this case the height of the stairs. Figure 9 shows the peak of the stance phase knee torque as a function of the stair height for healthy individuals, the baseline controller and that of a simulated controller that implements the context modulation.

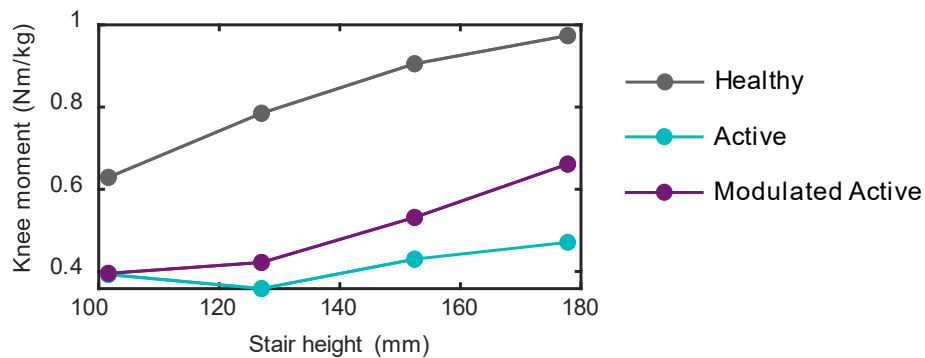


Figure 9: Knee torque during stair ascent task for healthy subjects and individuals with transfemoral amputation using a passive prosthesis and an active prosthesis. Healthy subjects exhibit modulation of torque for a change in condition of the stair height.

Quarter 2 Activities and Accomplishments:

Major Task 4: System Implementation

We have upgraded our real time machine learning system to be able to predict different locomotion modes with our best proposed algorithm (XGBoost) from our recently accepted paper. Once we are allowed to begin testing, we will conduct experimental protocols to implement a tiered machine learning controller that can couple classification and regression estimation. Different machine learning algorithms have been explored to estimate user state and environment information such as mode classification and continuous regression tasks such as slope estimation and stair height estimation. Furthermore, we are preparing two manuscripts: 1) a biomechanics paper on describing the effects of a powered vs. passive device for stair ascend and descend (Major Task 6), and 2) a speed independent slope estimator that can be implemented in general for wearable devices.

A manuscript has been accepted to the IEEE Robotics and Automation Letters (RA-L) titled “Machine Learning Model Comparisons of User Independent and Dependent Intent Recognition System for Powered Prostheses”. This paper highlights our efforts in the investigation of subject independent mode classifiers. We also had 2 abstracts accepted to the American Society of Biomechanics Annual Meeting 2020. One paper was titled “User and Speed Independent Slope Estimation for Lower-Extremity Wearable Devices”. The other was titled “Restoring Functional Gait of Individuals with Transfemoral Amputation using a Powered Prosthesis.

Last quarter, we were able to show that our real-time system was able to properly switch between modes during walking trials. This is promising as we continue to create and develop a real time user-independent system that can generalize across users. Future work will look at creating a tiered machine learning controller that can first predict walking modes followed by an environment estimator (i.e. stair height estimation and slope estimation).

One of the tasks we have been working on, include developing a speed and user independent slope estimator for applications in real-time lower-limb prosthetic and exoskeleton control. The collected sensor data was sectioned off to represent sensor suites commonly found in ankle prostheses, knee-ankle prostheses, and hip exoskeletons. Our goal is to develop a slope estimator for each sensor suite that would enable wearable assistive devices to appropriately scale joint torques.

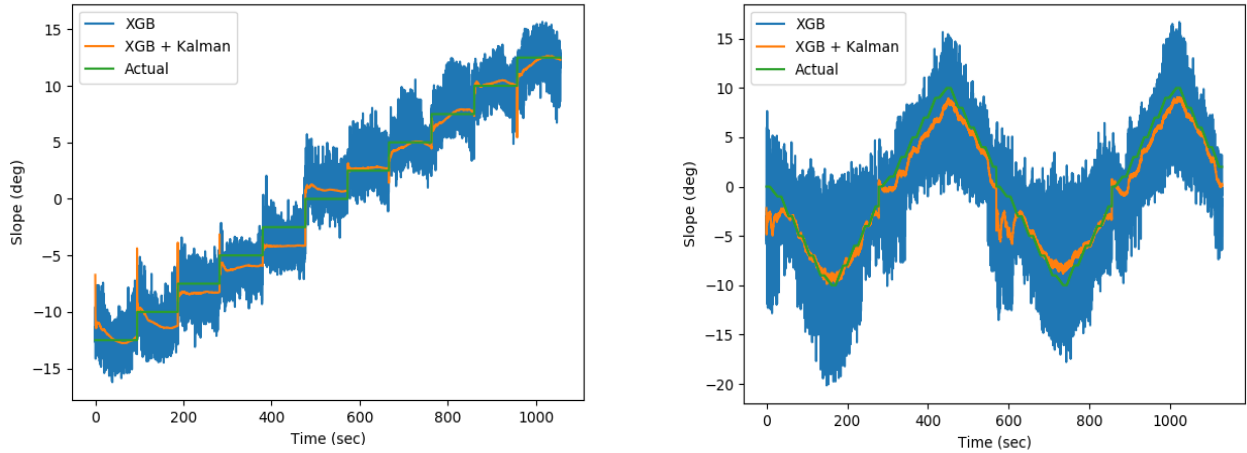


Figure 10: Static slope tracking for subject AB06 (left). The XGBoost model alone achieve a MAE of 1.21 ± 1.56 deg. The addition of a Kalman filter reduced errors to 0.5 ± 0.77 deg MAE. Dynamic slope tracking for subject AB06 (right). The XGBoost model alone achieve a MAE of 2.32 ± 3.00 deg. The addition of a Kalman filter reduced errors to 1.14 ± 1.23 deg MAE.

The above results were obtained by using the entire sensor suite. In our preliminary analyses, we determined that XGBoost machine learning models achieve optimal MAE errors when estimating slopes within quadruple-phase gait cycles. Subsequently, user-independent slope estimation of static and dynamic slopes was carried out for each subject. A Kalman filter was optimized and implemented to further reduce errors. We achieved optimal across-subject errors of 0.901 ± 1.935 and 1.640 ± 0.663 deg MAE for static and dynamic slope tracking, respectively. Figure 10 shows the slope estimation performance of the XGBoost model and XGBoost + Kalman model for one of the nine subjects. These results are promising as it shows that this algorithm can adapt to changes in slopes and walking speed simultaneously. This will allow us to take one step closer to adapting our prosthetic and exoskeleton controllers to better assist users in real-world tasks.

With the challenge in creating smart robotic prosthesis for the lower limb, machine learning based pattern recognition techniques have been shown to classify the ambulation mode in powered prostheses from mechanical sensors and neuromuscular signals, demonstrating the potential application in the control of the ambulation mode of prosthetic legs. However, most of the results in literature have focus on the evaluation of methods that are heavily subject dependent with limited evaluation of models that can generalize the intent recognition across different individuals. Furthermore, most of the studies limit to the evaluation to a fixed terrain that is individual stair height and ramp inclination. In our recently accepted manuscript we presented our investigation of the use of the XGBoost algorithm for developing a subject independent and dependent models. We evaluated the performance of XGBoost across different stair heights and inclination angles. Our findings suggest that XGBoost (Figure 12) offers a potential benefit for both subject independent and subject dependent algorithms outperforming LDA and NN (DEP SS Error: $2.93\% \pm 0.49\%$, DEP TS Error: $7.03\% \pm 0.74\%$, IND SS Error: $10.12\% \pm 3.16\%$, and IND TS Error: $15.78\% \pm 2.39\%$)($p < 0.05$). We observed that our model can predict the ambulation mode irrespective of the terrain characteristics that is stair height and ramp inclination with comparable results to the state-of-the-art. We created several confusion matrices (Figure 11) to show how the model performed across individual modes. Note LW data was present in both classifier types. We concatenated across subjects and combined steady state and transitional errors to show how XGBoost performed in classifying each mode.

In the DEP case, XGBoost correctly classified 3170/3227 (98.23%) level walking (LW) steps, 592/633 (93.52%) ramp ascent (RA) steps, 594/643 (93.8%) ramp descent (RD) steps, 400/421 (95.01%) stair ascent (SA) steps, and 268/299 (89.63%) stair descent (SD) steps. Overall, across all modes in the DEP case, XGBoost correctly classified 5024/5223 steps (96.19%). In the IND case, XGBoost correctly classified 3098/3227 (96.00%) level walking (LW) steps, 516/633 (81.52%) ramp ascent (RA) steps, 457/643 (71.07%) ramp descent (RD) steps, 391/421 (92.87%) stair ascent (SA) steps, and 233/299 (77.93%) stair descent (SD) steps. Overall, across all modes in the IND case, XGBoost correctly classified 4695/5223 steps (89.89%).

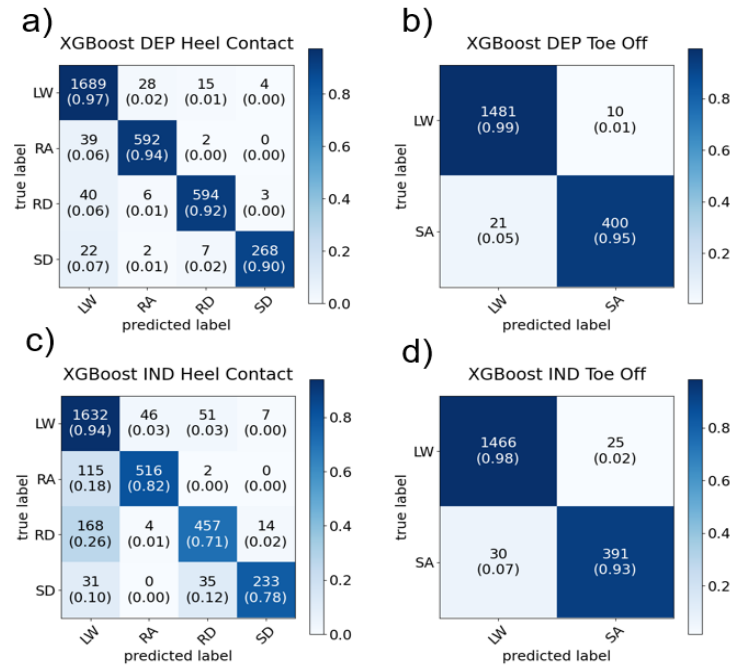


Figure 11: Confusion matrices for our best model (XGBoost) to show individual classification accuracies for each mode and phase type - (a) DEP HC classifier, (b) DEP TO classifier, (c) IND HC classifier, and (d) IND TO classifier). The results show that in the DEP case, XGBoost had a 96.19% classification accuracy and that in the IND case, XGBoost had a 89.89% classification accuracy. The y-axes show the true label while the x-axes show the predicted label.

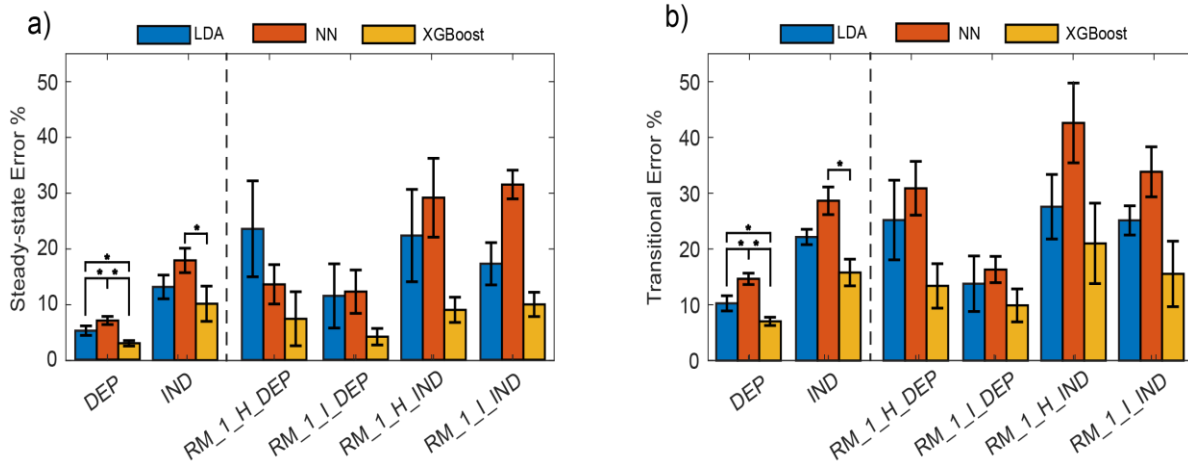


Figure 12: Three different models (LDA/NN/XGBoost) were compared for the classification of ambulation mode in ramps, stairs and level-ground, resulting in XGBoost outperforming other models. The y-axis shows the performance metric, consisting of the error in classification during steady state walking within a mode and the error of transitioning between modes. The x-axis show the six conditions of evaluation: subject dependent (i.e. training and testing on the same subject), subject independent (i.e. training on all subjects but the testing subject), and remove-1 condition for the stair height and ramp inclination for both (a) dependent and (b) independent. Error bars represent $\pm$ standard error of the mean. Asterisks indicate statistical significance ($p < 0.05$).

In tandem, we have also been working on creating continuous regressors for estimating environmental variables. Specifically, Figure 13 shows results for the stair height estimator using the XGBoost algorithm. When computing the error across all 4 presets/heights (4 – 7 in), we created separate models for stair ascend (SA) and stair descend (SD) separately and compared across both dependent and independent cases. For SA, the lowest error in the dependent (DEP) case was with a mean absolute error (MAE) of 1.23 ± 0.02 cm. In the independent case (IND), the lowest MAE error was 1.54 cm $\pm$ 0.05 cm. For SD, the lowest DEP error was 1.63 ± 0.11 cm and for IND was 1.91 ± 0.08 cm. These results are promising as they show that we can achieve decent estimated results for stair heights.

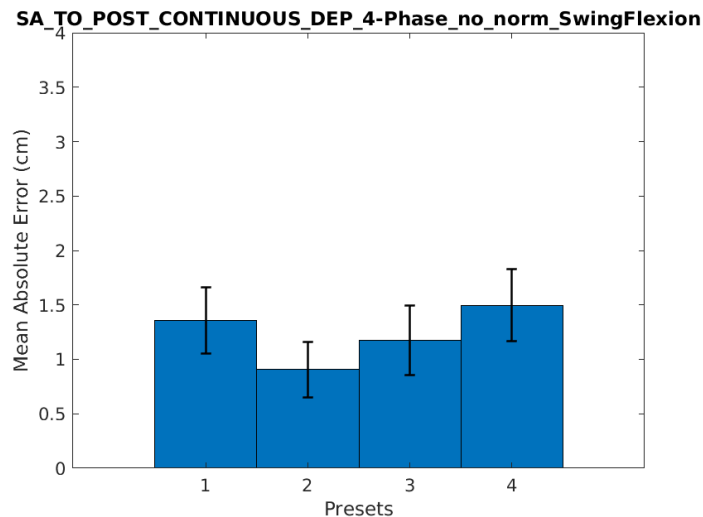


Figure 13: Stair height estimation using XGBoost. Mean absolute error from the stair height estimator shown for the dependent (DEP). It can be seen that these results show promise in being able to provide accurate estimation that can be embedded into our prosthetic controllers.

A similar analysis was also performed for walking speed estimation. The average error was computed across speeds for the dependent (DEP) and independent (IND) cases. The lowest error in the DEP case was 0.042 ± 0.001 m/s (Figure 14) and in the IND case was $0.060 \pm .001$ m/s. These results are promising in which future work, we can scale push off torque as a function of walking speed by adapting impedance parameters in our powered prosthetic leg.

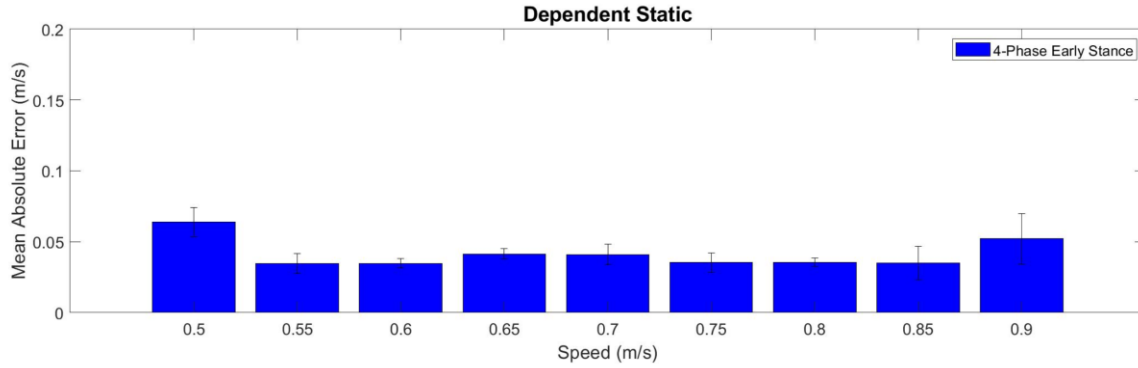


Figure 14: Walking speed estimation across 9 individual speeds in the DEP case. The best results were found looking at a 4-Phase model in the EarlyStance phase. The XGBoost algorithm is able to estimate the middle speeds well as these algorithms are more suited for interpolation compared to extrapolation. These results show promise in being able to accurately predict walking speed and can be used in future prosthetic controllers.

A separate analysis was done to understand how well the algorithm tracked the environmental variable as a function of time. Figure 15 shows the tracking profile for a given subject analyzed under the IND case. The base model mean absolute error was 0.077 ± 0.018 m/s. Utilizing a kalman filter, the results improved to a mean absolute error of 0.021 ± 0.014 m/s. This result indicates that the model is able to dynamically track walking speed compared to just steady state locomotion.

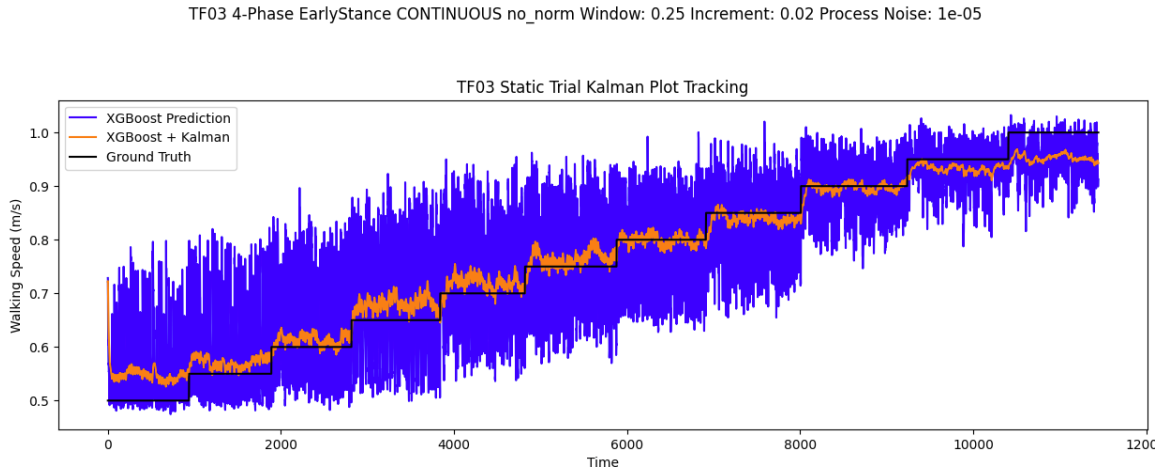


Figure 15: Walking speed estimation across 1 individual speeds in the IND case.

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

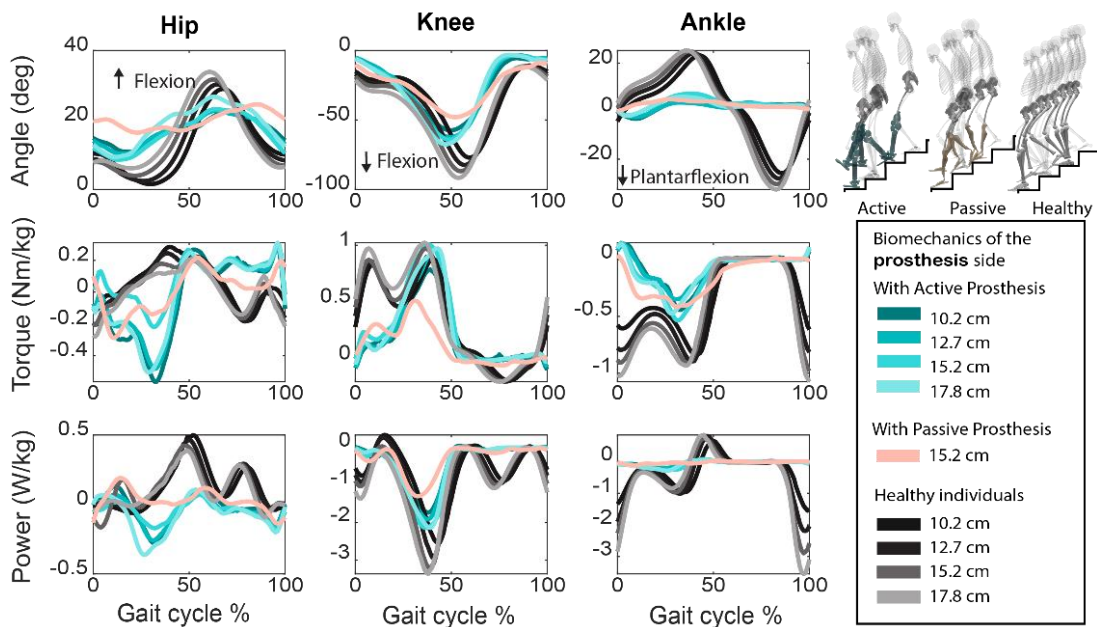


Figure 16: Biomechanics of the amputated leg with a powered prosthesis, passive prosthesis, and reference healthy data for stair descend across 4 different presets. The powered prosthesis can be seen to better resemble able-bodied individuals compared to the passive device.

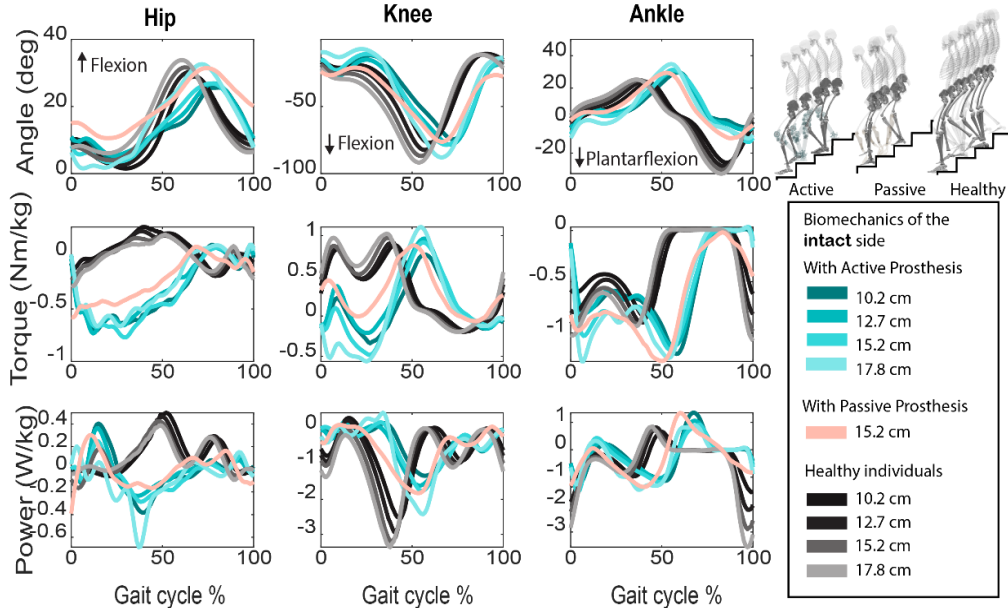


Figure 17: Biomechanics of the intact leg with a powered prosthesis, passive prosthesis, and reference healthy data for stair descend across 4 different presets. The powered prosthesis can be seen to better resemble able-bodied individuals compared to the passive device.

Stairs descent show reduced range of motion in all the joints in comparison to healthy subjects (Figures 16 and 17). For the active prosthesis, the knee flexion was limited by the hardware range of motion (70 deg). The active prosthesis produces knee extension torque during the stance phase in a similar magnitude that healthy subjects. The ankle provides significant torque with limited motion of the joint. The results present the absence of ankle dorsiflexion during stance phase. This is explained by the design choice of the tuning of the device to subject's preference. The kinematics of the sound side resembles that of healthy subjects. The range of motion of the hip shows a reduction in hip flexion for the non-amputated side when wearing a passive prosthesis. The knee joint shows knee flexion of the same magnitude of 73 deg. Future work will be done to perform context scaling with different stair heights. The prosthesis controller will use the estimated stair height (from Major Task 6) and be used as an input to this scaling equation that adapts torque through our impedance parameters. This will be the basis for our next experimental protocol in the future months.

The negative energy profiles for the stair descent strides was computed and averaged to determine the distribution of energy dissipation between the lower limb joints (Figure 18). For the cases of active, power, and healthy subjects the results show a similar magnitude of total negative power. The active prosthesis produces better symmetry of power distribution. With active prosthesis the prosthetic knee power absorption increases by 74% relative to passive prosthesis, producing a value close to such of healthy subjects.

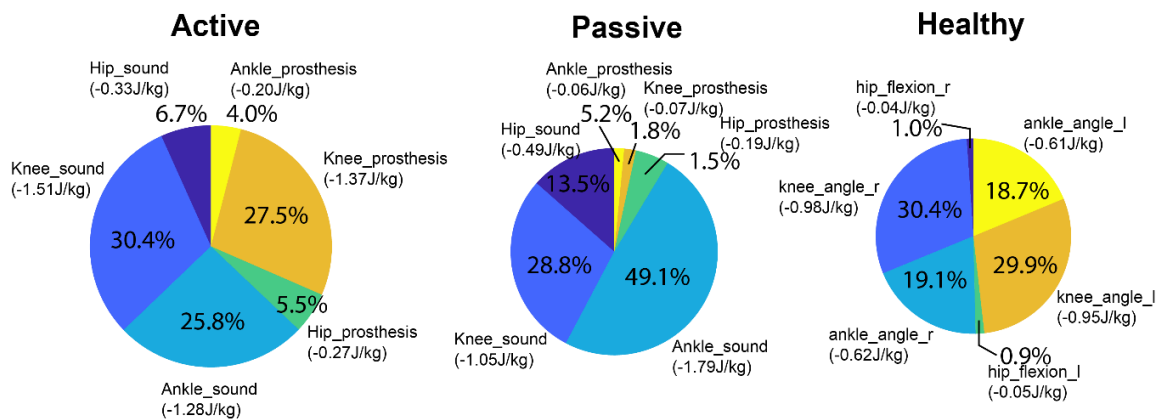


Figure 18: Average negative energy distribution during one stride of a stair descent task. Subjects were wearing the active prosthesis or a passive prosthesis. Healthy individuals are included as a reference for comparison with biological locomotion.

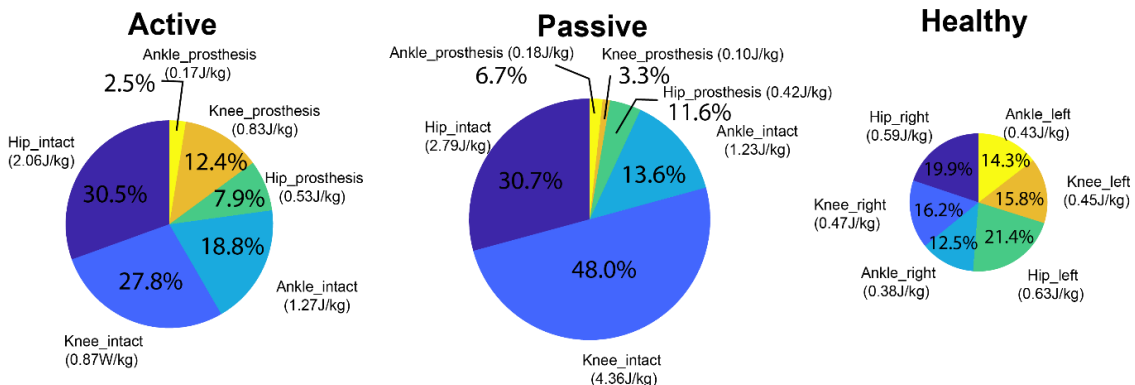


Figure 19: Average positive energy distribution for one progression of the stair ascent task. Subjects were wearing the active prosthesis or a passive prosthesis. Healthy individuals are included as a reference for comparison with biological locomotion. Note that with the passive prosthesis the subject executes two strides to achieve the same progression as a single stride with the active prosthesis.

Figure 19 presents the energy distribution of the stair ascent task. Both active and passive prostheses showed a reduced energy contribution with respect to healthy population. Furthermore, with the passive prosthesis, the prosthesis side provides negligible net energy at the knee and ankle joints, with the total energy given by the hip. The main contributor of the active prosthesis is the knee joint with 62% of the total energy of the prosthesis side followed by the hip joint with 31%.

Symmetry evaluation within subjects was performed using the asymmetry index for aggregated scalar results, with $ASI = 2(x_{prosthesis} - x_{intact}) / (x_{prosthesis} + x_{intact})$, in which 0% represents symmetry and $\pm 100\%$ implies total asymmetry. Figure 20 present the temporal characteristics of locomotion. This illustrates the alternating support of the prosthetic and intact side for the stair descent task. Temporal stance and swing asymmetry are present in both the active and passive with no significant difference. We found stance time ASI of -30.7% and -18.9% respectively. Swing time presented an ASI of 62.4% and 38.1% respectively. Similar analysis was also done for the prosthetic and intact side for the stair ascent task. Temporal stance and swing asymmetry are present in both the active and passive with no significant difference. We found stance time ASI to be -35.7% and -35.6% respectively, implying subjects spent more time with support on the intact side. Swing time presented an ASI of 68.4% and 65.9% respectively. From both Figures 20 and 21, it can be seen that the active leg is one step closer to resembling healthy gait by performing step-over-step patterns compared to step-to-step patterns.

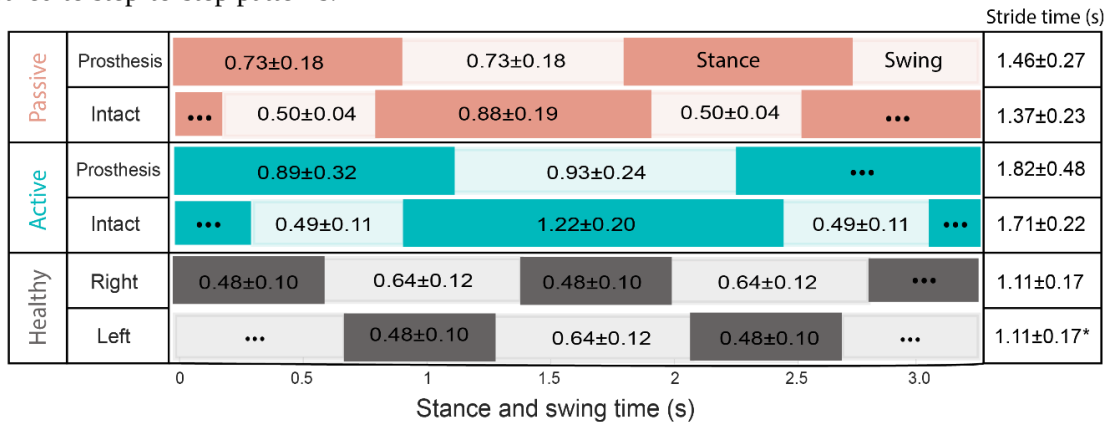


Figure 20: Temporal characteristics of stair descent locomotion with subjects wearing the active prosthesis and passive prosthesis. Stance times (dark color) and swing times (light color) $\pm$ standard deviation are presented in sequence, showing alternating support on the intact and prosthesis side.

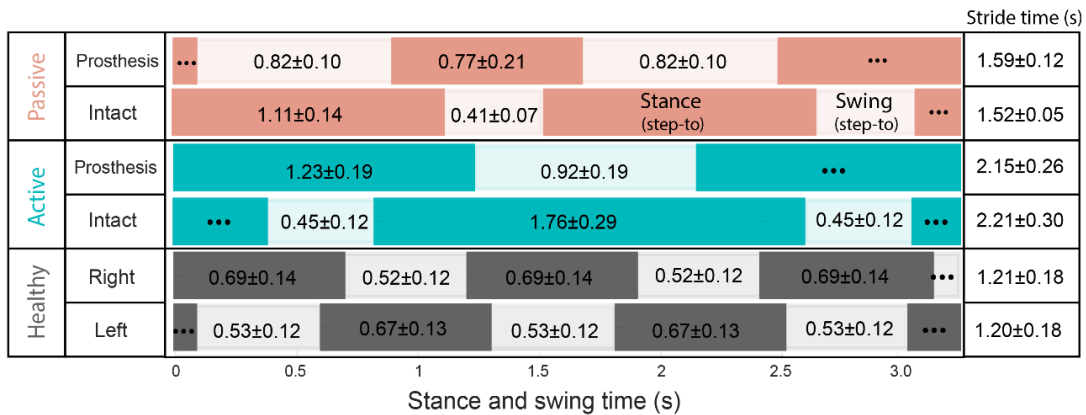


Figure 21: Temporal characteristics of stair ascent locomotion with subjects wearing the active prosthesis and passive prosthesis. Stance times (dark color) and swing times (light color) $\pm$ standard deviation are presented in sequence, showing alternating support on the intact and prosthesis side. Note that with the passive prosthesis the subject executes two strides to achieve the same progression as a single stride with the active prosthesis.

Quarter 3 Activities and Accomplishments:

Major Task 4: System Implementation

Our main goals have been to ensure our embedded controllers on the prosthetic device are robust to certain control and hardware issues we have encountered in the past as well as preparing several manuscripts. We performed additional machine learning analyses to improve upon our user independent system and are finalizing some of these results into three manuscripts we are preparing: 1) a biomechanics paper on describing the effects of a powered vs. passive device for stair ascend and descend (Major Task 6), and 2) a speed independent slope estimator that can be implemented in general for wearable devices, and 3) a walking speed estimation paper describing the impacts of our prosthetic sensors across a variety of validation cases.

In previous quarters, we were able to show that our real-time system was able to properly transition between modes during walking trials. This is promising as we continue to create and develop a real time user-independent system that can generalize across users. Future work will look at creating a tiered machine-learning controller that can first predict walking modes followed by an environment estimator (i.e. stair height estimation, slope estimation, or walking speed estimation) in online experiments.

One of the tasks we have been working on, include developing a speed and user independent slope estimator for applications in real-time lower-limb prosthetic and exoskeleton control. The collected sensor data was sectioned off to represent sensor suites commonly found in ankle prostheses, knee-ankle prostheses, and hip exoskeletons. Our goal is to develop a slope estimator for each sensor suite that would enable wearable assistive devices to appropriately scale joint torques.

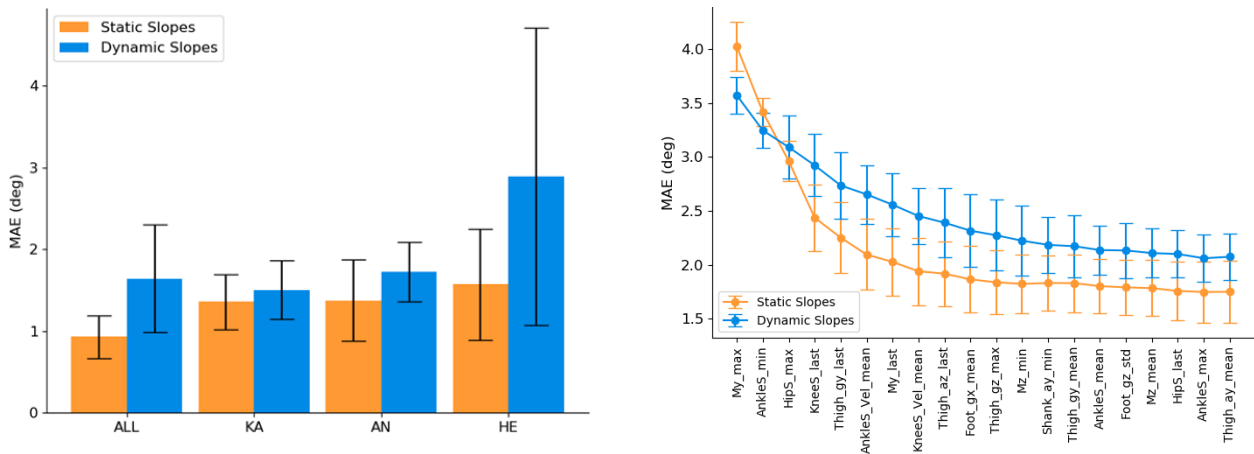


Figure 22: Cross-subject slope estimation performance on static and dynamic slopes (left). The best error was found to be 0.93 deg in the ALL case for static slopes and 1.50 deg in the KA case for dynamic slopes. Forward feature selection for the ALL case on static and dynamic slopes (right). The selection process found that approximately 20 features contributed to the greatest reduction of error.

User-independent machine learning models were trained and optimized for each subject using static data belonging to all other subjects. Models were evaluated on the static and dynamic data of the “novel” subject. Our analyses revealed that four XGBoost regression models (one for each phase of the gait cycle) paired with a Kalman filter yielded the best results. Parameter sweeps of learning rate, maximum depth, minimum child weight, gamma, and colsample bytree were conducted for each of the four models and averaged across subjects to obtain optimal and generalizable parameter sets for each device case (see Table 1-5). For the optimization of the Kalman filter, results for parameters sweeps of window size and process noise are shown in Table 5. It was interesting to find that cases that contained the least number of sensors optimized toward larger window sizes, as shown in Table 5. This may indicate that less sensor information requires a larger buffer a data to make reliable slope estimations.

The cross-subject performance of optimized regression models and Kalman filters on static and dynamic test data is shown in Figure 22. Slope level estimators for the ALL, knee-ankle prosthesis, ankle prosthesis, and hip exoskeleton cases respectively achieved error rates of 0.93°, 1.35°, 1.37°, and 1.57° MAE for static slopes and 1.64°, 1.50°, 1.73°, and 2.88° MAE for dynamic slopes. These results support our hypothesis that cases containing the most distal sensor information would perform the best given that prior work has primarily used foot and shank IMUs to estimate slopes via analog methods.

To further support our hypothesis, a feature selection analysis was conducted to determine the minimum number of features needed by the machine learning model to accurately estimate slopes. Figure 22 shows the 20 features that contributed the most to a reduction of error for the ALL case. Any additional features had little to no effect on reducing error rates. The most important sensors for slope estimation were shown to be the thigh inertial measurement unit (IMU), ankle goniometer (measures ankle angle) and the bertec treadmill’s force plates (measure ground reaction forces and moments). The inclusion of the ankle goniometer and force plates in the top 3 sensors list supports our previously mentioned hypothesis. It was interesting to find that the thigh IMU was the top performing sensor. The thigh IMU may provide rich information that relates slope level to vertical movements of the thigh. A case-specific sensor selection will be conducted for this scenario to confirm the usefulness and inform the possible exclusion of any sensor.

The combination of machine learning models with Kalman filters in this study has shown great promise in estimating static and dynamic slopes without the need for user-specific data or estimating walking speed. It was shown that distal sensors and sensors that encompass hip flexion motion during ambulation are of great importance to slope estimators. Our findings provide baseline architectures for accurately estimating slopes in knee-ankle prosthesis, ankle-prosthesis, and hip exoskeleton applications.

XGBoost Optimized Hyperparameters

Table 1: ALL case

Parameter/Gait Phase	0-25%	25-50%	50-75%	75-100%
Learning Rate	0.14	0.14	0.14	0.13
Max Depth	6	11	5	3
Min Child Weights	3	4	5	3
Gamma	0.20	0.13	0.16	0.18
Colsample Bytrees	0.48	0.39	0.57	0.52

Table 2: Knee-ankle prosthesis case

Parameter/Gait Phase	0-25%	25-50%	50-75%	75-100%
Learning Rate	0.14	0.17	0.12	0.10
Max Depth	5	10	3	8
Min Child Weights	3	4	4	4
Gamma	0.18	0.22	0.22	0.16
Colsample Bytrees	0.52	0.52	0.66	0.48

Table 3: Ankle prosthesis case

Parameter/Gait Phase	0-25%	25-50%	50-75%	75-100%
Learning Rate	0.14	0.14	0.13	0.10
Max Depth	6	10	5	12
Min Child Weights	5	2	2	4
Gamma	0.20	0.13	0.18	0.22
Colsample Bytrees	0.57	0.48	0.43	0.39

Table 4: Hip Exoskeleton case

Parameter/Gait Phase	0-25%	25-50%	50-75%	75-100%
Learning Rate	0.14	0.11	0.13	0.12
Max Depth	10	10	7	8
Min Child Weights	4	4	3	3
Gamma	0.31	0.28	0.27	0.22
Colsample Bytrees	0.52	0.57	0.52	0.48

Table 5: Kalman filter optimized parameters per case

Parameter/Case	AN	KA	HE	ALL
Window Length	250	100	400	200
Process Noise	1e-4	1e-5	1e-4	1e-4

Other machine learning analyses have also been explored to create a better gait parameter determination system in both dependent (DEP) and independent (IND) cases. We looked at creating a continuous walking speed estimation regressor to enhance our high-level controller embedded on the prosthetic device. Current state-of-the-art solutions involve using wearable sensors such as IMUs to estimate these parameters. However, previous studies have typically only evaluated their methods to static speeds. In this study, we investigated the use of different machine learning models for developing subject dependent and independent models across 6 individuals with transfemoral amputation. We evaluated the performance of these models across a variety of static walking speeds and dynamic speed trials. Our findings suggest that using machine learning models offers a potential benefit for both subject independent and subject dependent algorithms (DEP Error: 0.013 ± 0.001 m/s, IND Error: 0.057 ± 0.012 m/s, performing similarly to direct integration methods but with the advantage of real-time continuous determination especially in regards to dynamic ambulation conditions.

We were also able to show that with the inclusion of additional sensors, the model performance could be improved, indicating which sensors might be more useful in gait parameter determination. Our study provides valuable information for determining walking speed to make them more reliable across different users and robust to dynamic changes experienced in gait.

From the model comparison described above all ML models performed similarly in the standard DEP and IND cases, while LR was selected as the best model in the DYN and RM-1-S cases. Figure 23a displays the model evaluation using kalman filtered RMSE occurring in the optimal phase configuration for each model, representing the best possible performance of the given model in the given case scenario. XGBoost achieved the minimal DEP error at 0.013 ± 0.001 m/s, while NN achieved minimal IND error at 0.057 ± 0.012 m/s. LR performed optimally in all other cases achieving errors of: RM-1-S-DEP 0.024 ± 0.002 m/s; RM-1-S-IND 0.057 ± 0.007 m/s; DYN-DEP 0.057 ± 0.006 m/s; DYN-IND 0.058 ± 0.007 m/s.

A phase comparison of each ML algorithm was also performed to understand if there are specific locations during the gait cycle that would improve the determination of walking speed. The model output was combined with a Kalman filter for five different cases (Figure 23b). The results show for the best phase to select in the DEP case is the early stance phase with a RMSE of 0.014 ± 0.001 m/s for XGBoost. In the IND case, late stance shows the best for a subject-independent model with LR achieving an RMSE of 0.060 ± 0.007 m/s. Kalman filtering over the entire gait cycle led to errors of 0.0137 ± 0.001 m/s (DEP) and 0.068 ± 0.009 (IND). These results indicate that walking speed determination error varies over the gait cycle, and predicting selectively in certain phases can lead to a reduction in error.

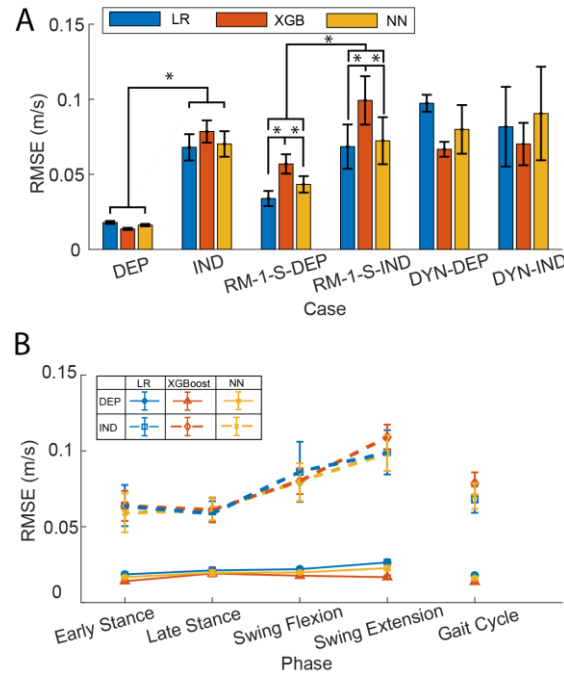


Figure 23: a) Three models (LR/NN/XGBoost) were compared for walking speed determination, resulting in LR outperforming other models in most cases. The y-axis shows the performance metric of average RMSE across subjects, evaluated for the model's optimal kalman filtered phase configuration for that case. The x-axis shows the six conditions of evaluation: subject dependent i.e. training and testing on the same subject, subject independent i.e. training on all subjects but the testing subject, remove-1-speed conditions for both DEP and IND, and dynamic conditions for both DEP and IND. Error bars represent $\pm$ standard error of the mean. b) A phase comparison was performed to understand if using a regressor at a specific section of the gait cycle could improve results. It was seen in the DEP case, that early stance and late stance models performed best, while in the IND case, the late stance model showed the best reduction of error.

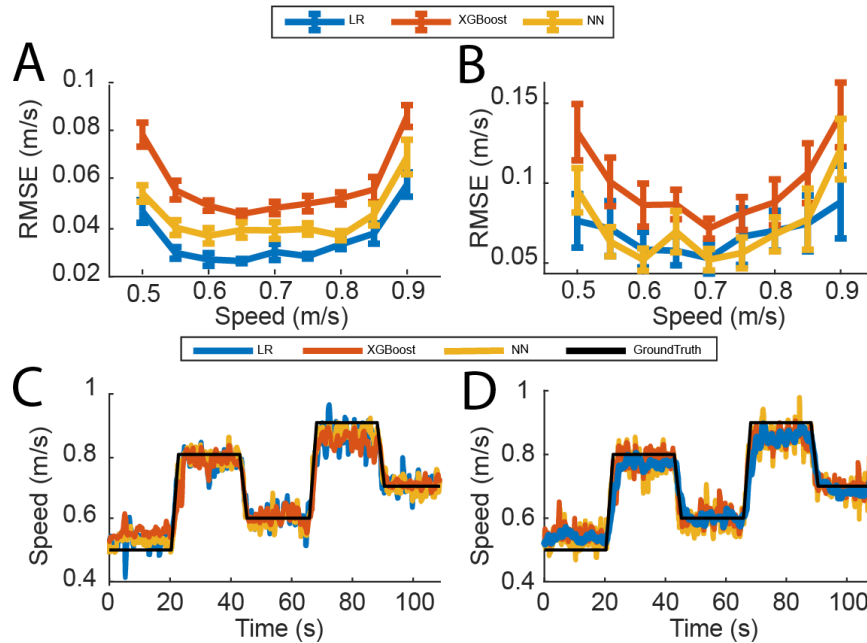


Figure 24: (a) and (b) show RMSE plotted across speed for the RM-1-S cases, with error bars representing the ± 1 standard error of the mean. In (c) and (d) dynamic trial tracking profiles are shown for each model with the solid black line indicating treadmill speed. The LR model showed the best performance across all 4 of these case studies.

LR was the best performer in the RM-1-S-DEP and RM-1-S-IND comparison. Figure 24(a,b) displays RMSE as a function of removed speed, where all models used a phase configuration of the entire gait cycle. LR performed best at the removal of 0.65 m/s in the DEP case at 0.025 ± 0.001 m/s, and best at 0.7 m/s in the IND case, at 0.053 ± 0.010 m/s. LR performed worst at the removal of 0.9 m/s in both cases, achieving 0.057 ± 0.005 m/s and 0.088 ± 0.021 m/s in DEP and IND cases respectively.

DEP Dynamic tracking performance, shown in Figure 24(c) was similar across models, with LR achieving a slight edge at 0.057 ± 0.006 m/s. LR performed stronger than other models in the IND case, Figure 24(d), achieving 0.058 ± 0.007 m/s. Time delay was calculated to determine each model's responsiveness to changes in speed. NN achieved the minimum average time delay in the DEP case of 132 ms. LR followed at 207 ms, and XGBoost performed worst with a delay of 241 ms on average. In the IND case, XGBoost performed best with a time delay of 264 ms. NN and LR obtained delays of 339 ms and 384 ms respectively. These delays are much shorter than one stride, the minimum time required to update most direct integration methods. Our approach showed that finding an optimal model complexity could improve model performance and generalize across not only static speeds but be able to dynamically determine changes in walking speed. Future work will continue to explore coupling a user intent recognition system that not only predicts locomotion mode, but also continuously determines environmental parameters synchronously.

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

We are developing a model for the Biomechanics analysis of TFA in OpenSim. This model is based on the Gait2354 model in OpenSim with a modified tibia and foot segments, replaced with the prosthesis. The model includes accurate measurements of mass properties and CAD-based estimation of moments of inertia.

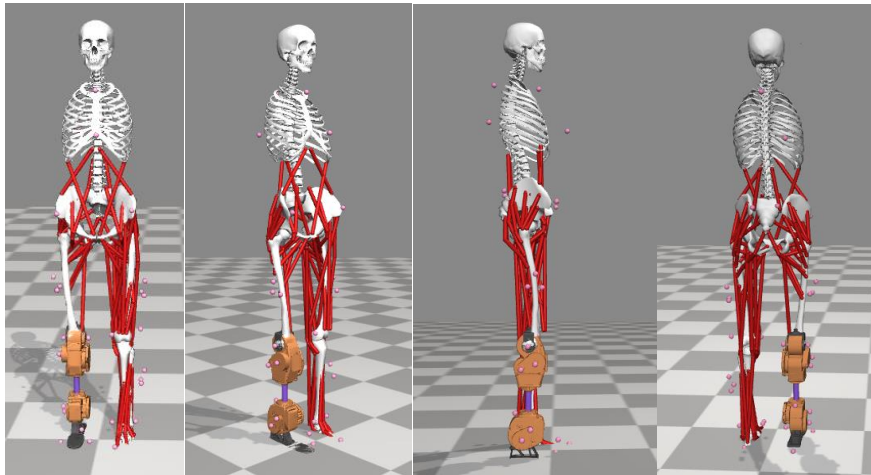


Figure 25: A model of the open-source powered knee and ankle prosthesis. The model includes the measured mass and center of mass parameters and CAD-based estimation of the moments of inertial.

We are performing a validation with the model with respect of the embedded sensors. The experimental trials consists of TFA subjects walking on a treadmill at 0.8m/s. We record the embedded sensors, forceplate data and motion capture markers. Preliminary results show accurate matching from the model kinematics and the joint angles measured with the joint encoders in the prosthesis (Figures 26-27). Similarly, consistently matching readings are observed in the forceplate data and the loadcell in the prosthesis (Figures 28).

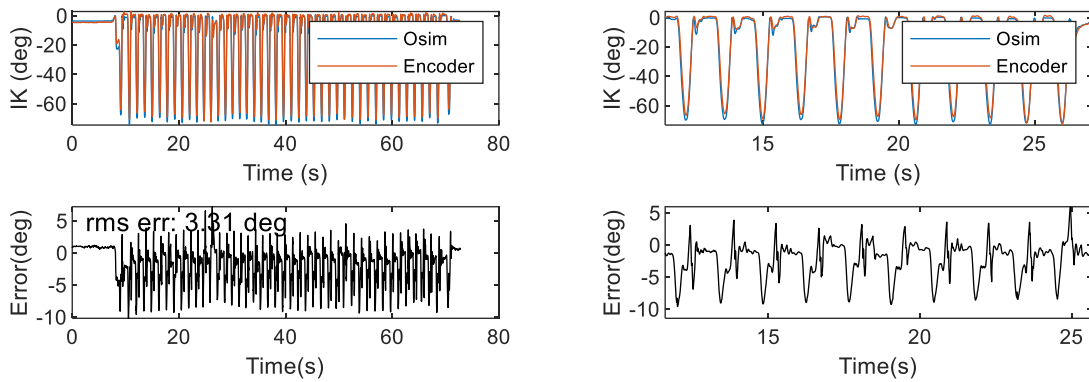


Figure 26: Knee angle (negative is flexion) measured from the joint encoder in the prosthesis in comparison to the output of the marker-based inverse kinematics from the OpenSim model. Both signals show the same response with RMSE of 3.3deg (2.8% range of motion).

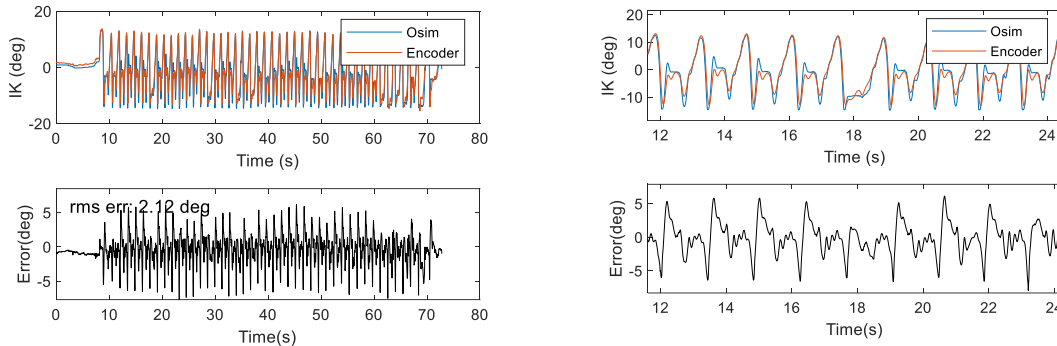


Figure 27: Ankle angle (negative is plantarflexion) measured from the joint encoder in the prosthesis in comparison to the output of the marker-based inverse kinematics from the OpenSim model. Both signals show the same response with RMSE of 2.12deg (7.1% range of motion)

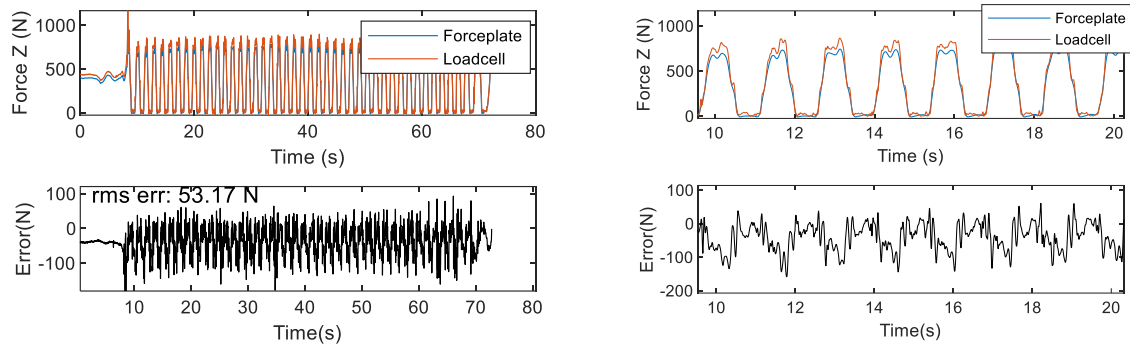


Figure 28: Vertical ground reaction force measured from the forceplate in the instrumented treadmill and the loadcell embedded in the powered prosthesis. Both signals show the same response with RMSE of 53.2N (6.7% body weight).



Figure 29: Recording from the experimental validation and reconstruction with the model.

As demonstrated, the model provides a good kinematics description of the TFA subject using the prosthesis. This provides an important tool for the analysis of the bilateral biomechanics. Future work will focus on the evaluation of the kinetics (i.e. joint moments) in comparison to the measurements of motor current and torque set-points.

Quarter 4 Activities and Accomplishments:

Major Task 4: System Implementation

Our most recent work has focused on 1) addressing hardware and software issues of the Open Source Leg (OSL) to ensure consistent and reliable data collection, 2) preparing a manuscript of our user- and speed-independent slope estimation methods, 3) addressing reviewers' comments regarding our submission of a walking speed estimator for knee-ankle prostheses applications, 4) and implementing linear relationships found between joint moments and stair height, slope level, and walking speed into our control system such that assistance may be scaled based on the environment.

The OSL is comprised of multi-belt gear trains that are rated for specific torque outputs. However, our long-term use of the OSL has resulted in the consistent breaking of belts under user load. In conjunction with the developers of the OSL, we found a solution to this issue which involved purchasing custom belts which were wider and sturdier. We have had no further belt issues since switching to the new belts. In addition to belt breaks, we experienced issues dealing with control instability stemming from the built-in controllers on our actuator packages. The update rates supported by the Raspberry Pi4 were too low to maintain steady-state current commands. As a solution, we shifted our controller to an Impedance Controller which accepts impedance parameters at a low update rate of 100 hz but implements current control at 10 khz.

We have also been working on a manuscript that will summarize our methodology for user-independent slope estimation across a variety of lower-limb wearable devices. Through a series of optimization steps, we will outline the best possible combination of sensors, sensor features, machine learning models, and Kalman filters for slope estimation in prosthesis and exoskeleton applications. As discussed in the previous report, we achieved error rates as low as 0.93° MAE when using a Kalman filter. To further reduce error rates, semi-dependent models were explored. For each test subject, a user-independent slope model was trained using slope data from all other subjects. Then, test subject data was incrementally added to the training set. As shown in Figure 30, across all subjects, error rates dropped by an average of 0.8° MAE when 10% of test subject data was added. Adding more test subject data did further reduce error rates, but not as significant as the drop seen at 10%. This preliminary analysis did not make use of a Kalman filter which may help further reduce errors. User-independent models are meant to serve as off-the-shelf solutions. Thus, the need to pre-collect additional data from a test subject is not practical. Due to these findings, we aim to explore user-independent models that can adapt, in real-time, to new incoming data of the novel user. Such a model would improve over time and would not require additional data to be collected in a lab setting.

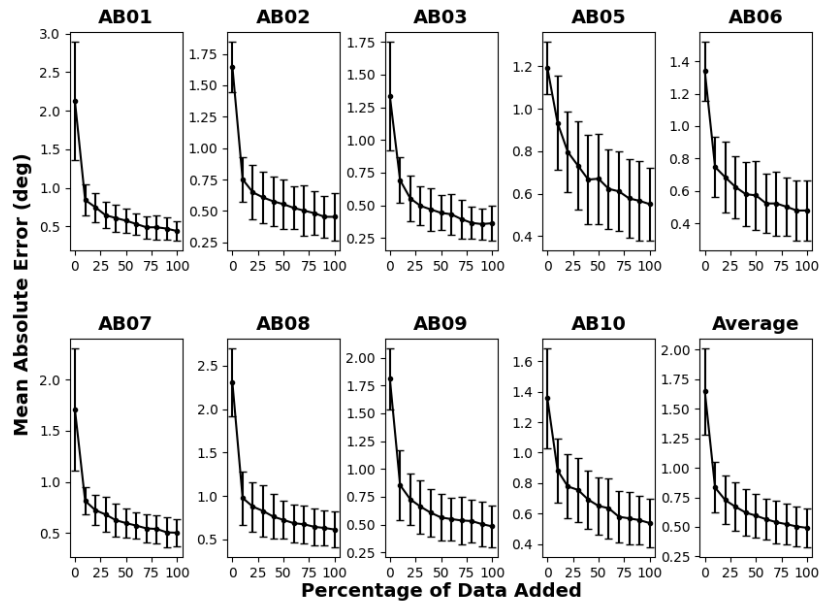


Figure 30: Slope estimation benefit of including novel user data after the training of user-independent models. The largest improvement in error rates can be seen at the 10% mark in which error rates drop by an average of 8° .

Since our last report, we have received reviewers' comments and have addressed them and are awaiting for a final decision on our manuscript. The title of manuscript has been updated to "Evaluation of Continuous Walking Speed Determination Algorithms and Embedded Sensors for a Powered Knee & Ankle Prosthesis". A quick synopsis of the manuscript was to evaluate continuous walking speed estimators embedded on a powered prosthesis. Our findings suggest that using machine learning models offers a potential benefit for both subject independent and subject dependent algorithms (DEP Error: 0.013 ± 0.001 m/s, IND Error: 0.057 ± 0.012 m/s, performing similarly to direct integration methods but with the advantage of real-time continuous determination especially in regards to dynamic ambulation conditions.

A sequential forward sensor selection revealed that in the DEP case, the inclusion of all sensors yielded the lowest Kalman filtered error; however, in the IND case, error leveled off and eventually increased as the final sensors were added. Figure 31 shows continually decreasing error in the DEP case, with the thigh IMU being the most important sensor; XGBoost was capable of achieving 0.025 ± 0.002 m/s from only this sensor. Adding the shank IMU and encoders added significant information, reducing XGBoost error to 0.016 ± 0.001 m/s. Further sensor addition contributed less to error reduction; in the DEP case, the thigh IMU was statistically more significant than each of the encoders, loadcell, and foot IMU ($p < 0.05$). The thigh and shank exhibit a similar relationship for XGBoost in the IND case, combining for optimal unfiltered error of 0.083 ± 0.002 m/s; further sensor addition was seen to increase error.

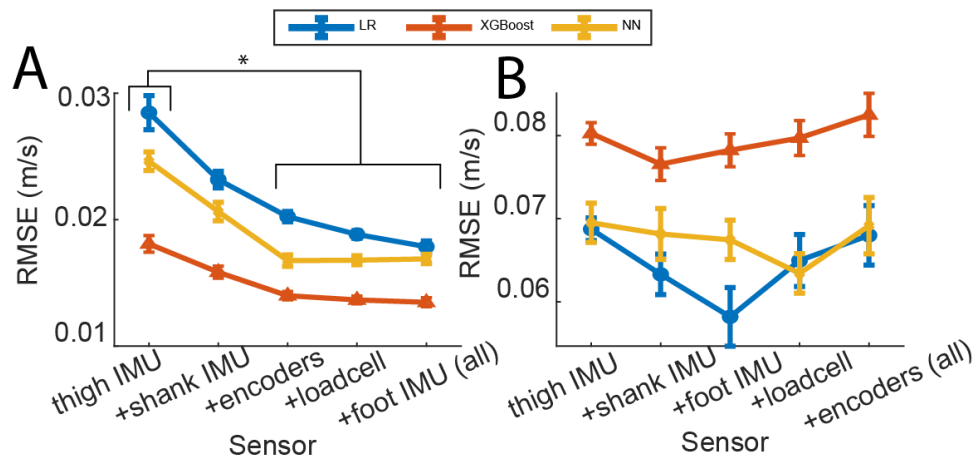


Figure 31: The optimal ML algorithm was selected to determine the sensor order using a sequential feature selection process. This was implemented for the remaining (A) subject dependent and (B) subject independent models. In both cases, the thigh IMU and shank IMU were the most favorable sensors for walking speed determination. The y-axes show the average RMSE across subjects for each condition, while the x-axes show the added sensor to the pool on each iteration. Error bars represent the $\pm$ standard error of the mean.

Furthermore, a comparison of computational costs was completed to show that these methods can indeed be performed in real-time and onboard a standard microprocessor. We measured the processing time it took to perform feature extraction and prediction using the 3 different models on a commercially available microprocessor (i.e. Raspberry Pi 4 Model B+ (4GB) with default settings). Linear regression showed the smallest computational time with 17.5 ± 2.9 ms, followed by XGBoost with 19.8 ± 4.4 ms, and lastly NN with 21.2 ± 4.7 ms. We know that hardware is different for many devices, but hope this can serve as a benchmark test for the field to ensure that our proposed algorithm may be viable to embed on a powered prosthesis in real-time. Some limitations to address in future work include in understanding the balance tradeoff between higher model accuracies versus amount of data required from a user. In this approach, the users walked for ~ 10 minutes in order to train a model. Additionally, by creating user-independent models, the need for gathering more data may be alleviated, as the model can generalize to patterns seen in other subjects.

Lastly, our analysis shows the baseline architectures of these machine learning algorithms for continuous walking speed determination. The following table displays the optimized parameters used in the NN and XGBoost models. The LR models require no parameters. In XGBoost, the set of hyperparameters explored included: the learning rate used to influence the convergence to a solution, the maximum allowable tree depth, the regularization term to control the sensitivity, and the number of estimators utilized to learn the data. Note, the early stopping functionality was utilized to prevent overfitting of the model. In NN, the set of hyperparameters included: layers and nodes to determine adequate size of the network needed, optimizer and learning rate to influence the convergence to a solution, and activation function and batch size to limit model complexity.

Previous studies have indicated that implementing these models in real-time is a must for robotic controllers to be utilized for clinical applications. Although, our study was limited to an offline analysis, our study demonstrates that walking speed determination can be done continuously throughout the gait cycle, which, if implemented in real-time, allows for control parameters to be updated instantly compared to waiting for a delayed system (e.g. waiting for the next stride), as would be necessary with direct integration. Future work will look to perform studies with an online system that incorporates real-time assistance scaling based on estimated parameters.

Table 6: Final optimized parameters.

	NN	XGBoost
Parameter Ranges	Layers: 1-3 Nodes: 10, 20, 30, 40, 50 Optimizer: <i>Adam</i> , <i>SGD</i> , & <i>RMSprop</i> Learning rate: 0.001, 0.005, 0.01 Activation function: <i>sigmoid</i> & <i>tanh</i> Batch size: 32, 64, 128	# of Estimators: 50, 100, 150, 200, 300 Max depth: 1, 3, 6, 9 Lambda: 0, 0.5, 1, 2, 4 Learning rate: 0.01, 0.05, 0.1, 0.3, 0.5
DEP	Layers: 1 Nodes: 40 Optimizer: <i>Adam</i> Learning rate: 0.001 Activation function: <i>sigmoid</i> Batch size: 128	# of Estimators: 300 Max depth: 6 Lambda: 0.5 Learning rate: 0.1
IND	Layers: 3 Nodes: 10 Optimizer: <i>SGD</i> Learning rate: 0.001 Activation function: <i>sigmoid</i> Batch size: 128	# of Estimators: 300 Max depth: 3 Lambda: 1 Learning rate: 0.3

We are currently running an experiment that will implement our speed estimation findings in real-time and scale assistance according to the linear relationships outlined in Figure 32. The study consists of collecting walking data on a Bertec Treadmill at constant speeds ranging from 0.4 – 1.0 m/s and at dynamic speeds that vary within the same range. User-dependent machine learning models are trained on all static trials and evaluated in real-time on dynamic trials. So far, we have completed N=1 subjects. We intend to collect data from an additional nine subject such that we can scale with and validate a user-independent speed estimator.

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

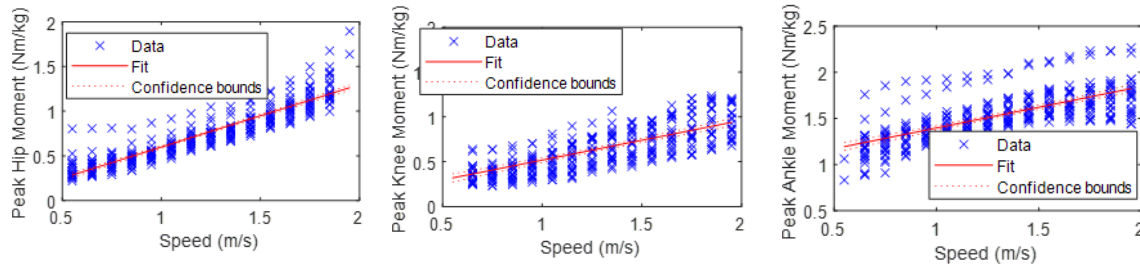


Figure 32: Linear regression models for peak joint moment during walking at different speeds. The moment consistently increases with the increase of walking speed ($p < 0.05$).

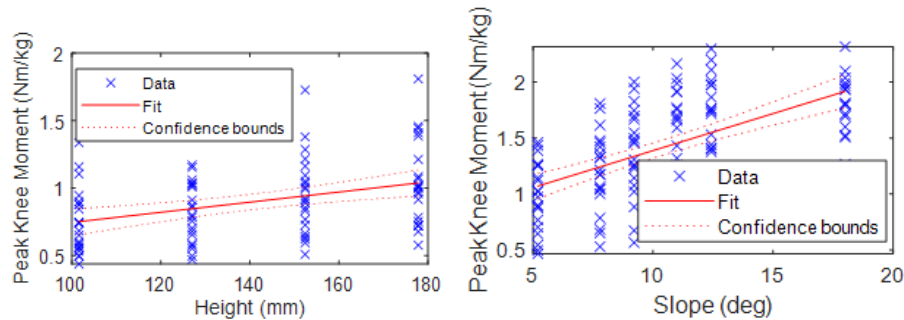


Figure 33: Linear regression models for peak knee moment during stair ascent at different stair heights (left) and ramp descent at different ramp inclines (right). The knee moment increases with the increase of stair height and ramp incline ($p < 0.05$).

We have explored the use of data from healthy subject's locomotion biomechanics to derive regression models that constitute the relationships between kinetic variables and the walking conditions. The regression evaluated the relationship between the peak sagittal moment for each lower limb joint with respect to walking speed for treadmill and ramp inclination or stair height for ambulation in ramps and stairs, respectively. As an example, Figure 32-33 Show some examples of the linear fit for multiple ambulation modes. Table 7. summarizes the results for every ambulation mode, presenting the resulting sensitivity to the gait state parameter as a percentage relative to the peak moment at a nominal condition. These regression models are critical for the development of controllers that have better awareness and response to multiple terrains. Using the relationship between the kinematics variable and the walking state parameter we can further tune the prosthesis control to better mimic the biomechanics of the healthy population. For example, since the knee during stair ascent shows an increase of 0.44% of moment for a 1mm increase in stair height, a controller can use the information from stair height detection and if found that the stairs are 7cm over the nominal condition, it can adjust the moment by increasing the nominal response by 30.8%.

Table 7: Regression model results for peak moment with respect to gait state parameter conditions in multiple ambulation modes. The data shows the slope of the linear model as a percentage relative to the peak moment at the nominal condition. N/A marks models that did not show significance.

Ambulation (nominal)	Hip	Knee	Ankle
Stair ascent (127mm)	N/A	0.44%/mm	N/A
Stair descent (127mm)	N/A	N/A	N/A
Ramp ascent (7.78deg)	6.82%/deg	N/A	N/A
Ramp descent (7.78deg)	N/A	5.33%/deg	N/A
Treadmill (1.35m/s)	8.29%/0.1m/s	6.57%/0.1m/s	2.89%/0.1m/s

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?

Dissemination of our research was more difficult this year than in previous years due to the impact of COVID-19 and our inability to hold outreach activities and host visitors. Our main avenue of dissemination was through various conferences which are included in the appendix but this include the P&O academy meeting, American Society for Biomechanics, and IEEE IROS. This allowed the team to still disseminate and convey the main scientific findings of the prosthesis work at relevant clinical, scientific and engineering conferences that have stakes in this technology development effort.

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

1. We will continue experimental testing throughout the end of the semester in accordance to the Institute's policy on the pandemic. We will submit several journal papers in the next quarter for both the biomechanics and machine learning components from the large data set already collected on the original powered prosthesis.

2. We will complete a short study that validates our biomechanics model of our prosthetic limb using our OpenSim pipeline. This will help facilitate comparisons to other groups utilizing the open source leg and comparing its biomechanical functions.
3. 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. We will test our coupled machine learning approach by predicting locomotion mode and determining appropriate environmental variables to dynamically scale assistance in the context of different locomotion tasks. This will also be an initial start of allowing our embedded controllers to perform this task in real-time.
4. We have begun looking at more clinical outcome measures such as preferred versus maximum walking speed, circuit completion time, and measures of effort on both powered and passive devices.
5. We will complete a short study that will lead to the development and validation of a sit-to-stand controller. This mode is to be added to the pool of modes that the prosthesis could autonomously predict.
6. We will incorporate an external attitude estimator/IMU to our system that will provide environmental estimations for adaptive models and improve intention recognition accuracy.

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

The COVID-19 pandemic presented setbacks which delayed research progress. In accordance with Georgia Tech policy, all students and faculty were instructed to limit on-campus research activities starting in March 2020. It took about 3 months for Georgia Tech to allow the ramp up of research activities on campus. During those three months we worked on advancing the control system of the Open Source Leg (OSL). With added precautions, experiments with amputees resumed soon after early in the fall semester. We experienced additional setbacks with the consistent breaking of OSL belts during experiments. We traveled to the University of Michigan to meet with the researchers that designed the OSL to address this issue. We gained insight on belt tightening techniques and arrived at the solution to order custom belts of higher quality and wider profile. Since receiving the new belts, we have not had any belts breaks. COVID-19 had major impacts in slowing down research during CY2020, but the team conserved funds and plans to finish the project over the next year.

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

Significant changes in use of biohazards and/or select agents

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 dealing with the implementation of an impedance controller in a knee-ankle prosthesis was published to AMSUS’s Military Medicine Journal in January 2020. A second journal paper was published in IEEE Robotics and Automation Letters, in July 2020 comparing the performances of machine learning models used in intention recognition systems for powered prosthesis. Two abstracts were published in the American Society of Biomechanics Conference 2020 proceedings and presented as posters in August 2020. The first abstract summarized a study investigating the benefits of using a powered transfemoral prosthesis over a passive one. The second abstract detailed slope estimation methods for wearable devices. We have one paper currently under review for publication (submitted October 2020) in the IEEE Robotics and Automation Letters Journal that describes speed estimation methods for lower-limb prosthesis. A paper, also under review, was submitted to IEEE Transaction on Medical Robotics and Bionics in November 2020 that provides a biomechanical analysis of transfemoral stair locomotion on powered and active prostheses. An abstract was submitted to the American Academy of Orthotists and Prosthetists in December 2020 detailing a comparison between patient reported outcomes when using a passive and powered prosthesis on ramps and stairs.

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

Nothing to report

Other publications, conference papers, and presentations.

- 1) Our journal paper was officially accepted to the AMSUS Military Medicine Journal in December 2019 and published in January 2020. The paper is titled “Impedance Control Strategies for Enhancing Sloped and Level Walking Capabilities for Individuals with Transfemoral Amputation Using a Powered Multi-Joint Prosthesis.” This paper describes a validation study involving the implementation of an impedance controller on our first version of a knee-ankle prosthesis. The authors are listed as follows: Krishan Bhakta, Jonathan Camargo, Pratik Kunapuli, Lee Childers, Aaron Young (PI). (See Appendix A).
- 2) Our journal paper submission to IEEE Robotics and Automation Letters was published in July 2020. The paper is titled “Machine Learning Model Comparisons of User Independent & Dependent Intent Recognition Systems for Powered Prostheses.” The paper focuses on the use of an XGBoost machine learning model to classify mode transitions for powered prostheses. The authors are listed as follows: Krishan Bhakta, Jonathan Camargo, Luke Donovan, Kinsey Herrin, and Aaron Young (PI). (See Appendix B). Krishan Bhakta presented a talk on this work during the International Conference on Intelligent Robots and Systems.
- 3) We submitted an abstract to the American Society of Biomechanics Virtual Conference (hosted at Georgia Tech) in August 2020. The abstract was titled “Restoring Functional Gait of Individuals with Transfemoral Amputation using a Powered Prosthesis.” The study sought to investigate the biomechanical benefits of using a powered prosthesis over a passive prosthesis. The authors are listed as follows: Krishan Bhakta, Jonathan Camargo, William Compton, Kinsey Herrin, and Aaron Young (PI). (See Appendix C). Krishan Bhakta presented a poster on this work at the conference.
- 4) We submitted an abstract to the American Society of Biomechanics Virtual Conference (hosted at Georgia Tech) in August 2020. The abstract was titled “User- and Speed-Independent Slope Estimation for Lower Extremity Wearable Devices.” The abstract detailed our initial analyses in developing robust slope estimators for a variety of lower-limb wearable devices. The authors are listed as follows: Jairo Maldonado, Krishan Bhakta, Jonathan Camargo, and Aaron Young (PI). (See Appendix D). Jairo Maldonado presented a poster on this work at the conference.
- 5) Our paper titled “Continuous Walking Speed Determination for Individuals with Transfemoral Amputation using a Powered Prosthetic Device” was submitted to IEEE Robotics and Automation Letters in October 2020. The paper is currently under review. It summarizes our methods for developing a walking speed estimator using sensor data from a lower-limb prosthesis. The authors are listed as follows: Krishan Bhakta, Jonathan Camargo, William Compton, Kinsey Herrin, and Aaron Young (PI). This paper will be included in future reports.
- 6) A journal paper titled “Stair ambulation with an active knee and ankle prosthesis: a step forward towards biologically inspired biomechanics,” was submitted to IEEE Transaction on Medical Robotics and Bionics in November 2020 and is currently under review. This paper describes a biomechanical study of stair ambulation between non-amputee and amputee population using passive and active prosthesis. The authors are listed as follows: Jonathan Camargo, Krishan Bhakta, Kinsey Herrin, and Aaron Young (PI).

- 7) We submitted an abstract to the American Academy of Orthotists and Prosthetists in December 2020. The abstract was titled “A pilot study comparison of patient reported outcomes following use of a powered knee-ankle prosthesis and clinically prescribed passive prosthesis on variable terrains.” The abstract details a comparison between patient reported outcomes when using a passive and powered prosthesis on ramps and stairs. The authors are listed as: Kinsey Herrin, Krishan Bhakta, Jonathan Camargo, and Aaron Young (PI). (See Appendix E).

- **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 Open Source Leg to both mechanical and electronic systems embedded on the device. For mechanical improvements, we have replaced old belts with wider, better quality belts that can sustain desired assistance levels under heavy load. In the occurrence that a belt does fail, we have manufactured a copy of the knee unit and are planning to do the same for the ankle unit. These backups would enable us to resume experiments minutes after any belt break. For the electronics, we have upgraded to a Raspberry Pi 4 with 8GB RAM to handle more computation which is critical when running real-time machine learning applications. A switch from a current controller to an impedance controller has shown major improvements in control stability that should lead to subjects trusting the device more.

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

Nothing to report

- **Other Products**

Nothing to report

7. PARTICIPANTS & OTHER COLLABORATING ORGANIZATIONS

<i>Name:</i>	<i>Aaron Young</i>
<i>Project Role:</i>	<i>PI</i>
<i>Researcher Identifier:</i>	
<i>Nearest person month worked:</i>	<i>9</i>
<i>Contribution to Project:</i>	<i>No change</i>

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: 5.25

Contribution to Project: No change

Name: Krishan Bhakta

Project Role: Graduate Student

Researcher Identifier:

Nearest person month worked: 51

Contribution to Project: No change

Name: Jonathan Camargo-Leyva

Project Role: Graduate Student

Researcher Identifier:

Nearest person month worked: 51

Contribution to Project: No change

Funding Support: Fullbright Fellowship

Name: Jairo Maldonado-Contreras

Project Role: Graduate Student

Researcher Identifier:

Nearest person month worked: 16

Contribution to Project: No change

Name: Sixu Zhou

Project Role: Master's 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: 3
Contribution to Project: No change
Funding Support: PURA Fellowship

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

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

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

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

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

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

Name: Kevin Edwards
Project Role: Undergraduate Researcher
Researcher Identifier:
Nearest person month worked: 2

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

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

Name: Noah Cho
Project Role: Undergraduate Researcher
Researcher Identifier:
Nearest person month worked: 7
Contribution to Project: No change

Name: Pratik Kunapuli
Project Role: Undergraduate Researcher
Researcher Identifier:
Nearest person month worked: 5
Contribution to Project: No change

Name: Stephen Mock
Project Role: Undergraduate Researcher
Researcher Identifier:
Nearest person month worked: 1
Contribution to Project: No change

Name: Ji Bok
Project Role: Undergraduate Researcher
Researcher Identifier:
Nearest person month worked: 9
Contribution to Project: No change

Name: Daniel de Matheu
Project Role: Undergraduate Researcher
Researcher Identifier:
Nearest person month worked: 13
Contribution to Project: No change

Name: Divya Chowbey
Project Role: NSF SURE Robotics Program Undergraduate Researcher
Identifier:
Nearest person month worked: 2
Contribution to Project: No change

Name: Darren Maguire
Project Role: Undergraduate Researcher
Researcher Identifier:
Nearest person month worked: 2
Contribution to Project: No change

Name: Jaeyoon Kim
Project Role: Undergraduate Researcher
Researcher Identifier:
Nearest person month worked: 2
Contribution to Project: No change

Name: Christian Croxton
Project Role: Undergraduate Researcher
Researcher Identifier:
Nearest person month worked: 1
Contribution to Project: No change

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

Name: Luke Donovan
Project Role: Undergraduate Researcher
Researcher Identifier:
Nearest person month worked: 7
Contribution to Project: No change

Name: Joel Bartlett
Project Role: Undergraduate Researcher
Researcher Identifier:
Nearest person month worked: 1
Contribution to Project: No change

Name: Ian Cullen
Project Role: Undergraduate Researcher
Researcher Identifier:
Nearest person month worked: 8
Contribution to Project: No change

Name: Hyeri Lee
Project Role: Undergraduate Researcher
Researcher Identifier:
Nearest person month worked: 5
Contribution to Project: No change

<i>Name:</i>	<i>Tarun Maddali</i>
<i>Project Role:</i>	<i>Undergraduate Researcher</i>
<i>Researcher Identifier:</i>	
<i>Nearest person month worked:</i>	<i>1</i>
<i>Contribution to Project:</i>	<i>No change</i>
<i>Name:</i>	<i>Jazmine Nash</i>
<i>Project Role:</i>	<i>Undergraduate Researcher</i>
<i>Researcher Identifier:</i>	
<i>Nearest person month worked:</i>	<i>3</i>
<i>Contribution to Project:</i>	<i>No change</i>
<i>Name:</i>	<i>Robert Belovodskij</i>
<i>Project Role:</i>	<i>Undergraduate Researcher</i>
<i>Researcher Identifier:</i>	
<i>Nearest person month worked:</i>	<i>1</i>
<i>Contribution to Project:</i>	<i>No change</i>
<i>Name:</i>	<i>Alexandra Eichinger-Wiese</i>
<i>Project Role:</i>	<i>NSF SURE Robotics Program Undergraduate Researcher</i>
<i>Identifier:</i>	
<i>Nearest person month worked:</i>	<i>2</i>
<i>Contribution to Project:</i>	<i>No change</i>
<i>Name:</i>	<i>William Compton</i>
<i>Project Role:</i>	<i>Undergraduate Researcher</i>
<i>Researcher Identifier:</i>	
<i>Nearest person month worked:</i>	<i>7</i>
<i>Contribution to Project:</i>	<i>No change</i>
<i>Name:</i>	<i>Gabriel Wilson</i>
<i>Project Role:</i>	<i>Undergraduate Researcher</i>
<i>Researcher Identifier:</i>	
<i>Nearest person month worked:</i>	<i>4</i>
<i>Contribution to Project:</i>	<i>No change</i>
<i>Name:</i>	<i>Gursimran Singh</i>
<i>Project Role:</i>	<i>Undergraduate Researcher</i>
<i>Researcher Identifier:</i>	
<i>Nearest person month worked:</i>	<i>1</i>
<i>Contribution to Project:</i>	<i>No change</i>
<i>Name:</i>	<i>Sudarshan Sundar</i>
<i>Project Role:</i>	<i>Undergraduate Researcher</i>
<i>Researcher Identifier:</i>	
<i>Nearest person month worked:</i>	<i>2</i>
<i>Contribution to Project:</i>	<i>No change</i>

Name: Sarah Deiters
Project Role: Undergraduate Researcher
Researcher Identifier:
Nearest person month worked: 2
Contribution to Project: No change

Name: Jeongwoo Cho
Project Role: Undergraduate Researcher
Researcher Identifier:
Nearest person month worked: 2
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.

Organization Name: University of Michigan

Location of Organization: Ann Arbor, Michigan

Partner's contribution to the project: Collaboration. Dr. Rouse and his group designed the Open Source Leg. We work closely with his group to address any mechanical design oversights we discover during use.

8. SPECIAL REPORTING REQUIREMENTS

COLLABORATIVE AWARDS: N/A

QUAD CHARTS: Attached as a separate document.

9. APPENDICES:

Appendix A: AMSUS Military Medicine Journal Paper

Appendix B: IEEE Robotics and Automation Letters Journal Paper

Appendix C: American Society of Biomechanics Abstract #1

Appendix D: American Society of Biomechanics Abstract #2

Appendix E: American Academy of Orthotists and Prosthetists Abstract

Appendix A: AMSUS Military Medicine Journal Paper

Title: Impedance Control Strategies for Enhancing Sloped and Level Walking Capabilities for Individuals with Transfemoral Amputation Using a Powered Multi-Joint Prosthesis

Authors: Krishan Bhakta, Jonathan Camargo, Pratik Kunapuli, Lee Childers, and Aaron Young

Date of Publication: December 9, 2019

Impedance Control Strategies for Enhancing Sloped and Level Walking Capabilities for Individuals with Transfemoral Amputation Using a Powered Multi-Joint Prosthesis

Krishan Bhakta, MS ^{*}; Jonathan Camargo, MS ^{*†}; Pratik Kunapuli, BS[‡];
Lee Childers, PhD, CP ^{§||}; Aaron Young, PhD^{*†}

ABSTRACT Introduction: Powered prostheses are a promising new technology that may help people with lower-limb loss improve their ability to perform locomotion tasks. Developing active prostheses requires robust design methodologies and intelligent controllers to appropriately provide assistance to the user for varied tasks in different environments. The purpose of this study was to validate an impedance control strategy for a powered knee and ankle prosthesis using an embedded sensor suite of encoders and a six-axis load cell that would aid an individual in performing common locomotion tasks, such as level walking and ascending/descending slopes. Materials and Methods: Three amputees walked on a treadmill and four amputees walked on a ramp circuit to test whether a dual powered knee and ankle prosthesis could generate appropriate device joint kinematics across users. Results: Investigators found that tuning 2–3 subject-specific parameters per ambulation mode was necessary to render individualized assistance. Furthermore, the kinematic profiles demonstrate invariance to walking speeds ranging from 0.63 to 1.07 m/s and incline/decline angles ranging from 7.8° to 14°. Conclusion: This work presents a strategy that requires minimal tuning for a powered knee & ankle prosthesis that scales across a nominal range of both walking speeds and ramp slopes.

INTRODUCTION

People with a transfemoral amputation using traditional passive prostheses ambulate with a variety of walking abnormalities. These individuals experience asymmetric loading between the intact and residual limb joints.¹ Certain individuals also suffer from chronic leg and back pain.² A goal in transfemoral prosthesis design has been to restore the lost function from both the knee and ankle joints. However, the vast majority of currently available prosthetic feet (e.g., Össur Vari-flex foot) and knees (e.g., Ottobock's C-Leg and Össur's Rheo Knee) are passive (i.e., provides no net power).^{3,4} The use of resulting compensatory strategies to walk that include greater moments on the intact limb may lead to joint degradation, pain, and osteoarthritis.^{1,5–7} Development of actively controlled powered prosthetic joints may reduce these post-amputation compensatory strategies.^{8–10}

Prosthetic hardware has been designed to alleviate and provide powered assistance to the user under different

locomotion tasks.^{11–17} However, creating a controller that can coordinate knee and ankle joints to provide the appropriate amount of assistance/resistance has been challenging.^{18–20} An additional consideration is ensuring that two independently powered joints can be controlled in unison to have efficient and stable dynamics. Various controllers have also been tested to improve functionality and robustness of these devices during dynamic movements.^{14,21–26} Impedance controllers implemented on powered transfemoral prostheses were among the first controllers to provide stable and coordinated user interaction with the environment.^{27,28} Using an impedance controller paired with a finite-state machine, which identifies critical points in the gait cycle, allows for the easy configuration of parameters to adjust gait for different tasks.⁸

Different research groups have developed their own prosthetic devices to help individuals with amputation, showing mechanical improvements over time; however, creating robust and smart controllers for dynamic activities is still underexplored.^{13,16,27} To achieve lower cost and weight requirements, some research groups have focused on single-joint prostheses and semi-active prostheses to improve common walking tasks without the need of bulky power sources.^{16,29} A challenge with powered multi-joint prosthetic systems has always been the integration of a sensor suite with a control system that can recognize different tasks and environments the person is walking in and responding accordingly. We have developed a powered knee-ankle prosthesis and control testbed by starting with a well-defined task (e.g., steady-state walking) where the intent of the user is known before progressing to more complex tasks (overground walking, ramps, stairs, etc.). In this development

^{*}Woodruff School of Mechanical Engineering, College of Engineering, Georgia Institute of Technology, Atlanta, GA USA

[†]Institute for Robotics and Intelligent Machines, Georgia Institute of Technology, Atlanta, GA USA

[‡]School of Electrical and Computer Engineering, College of Engineering, Georgia Institute of Technology, Atlanta, GA USA

[§]Center for the Intrepid, Department of Rehabilitation Medicine, Brooke Army Medical Center, JBSA Ft. Sam Houston, TX, USA

^{||}Extremity Trauma and Amputation Center of Excellence, JBSA Ft. Sam Houston, TX, USA

Corresponding author: walter.l.childers.civ@mail.mil
doi:10.1093/milmed/usz229

Published by Oxford University Press on behalf of the Association of Military Surgeons of the United States 2020. This work is written by (a) US Government employee(s) and is in the public domain in the US.

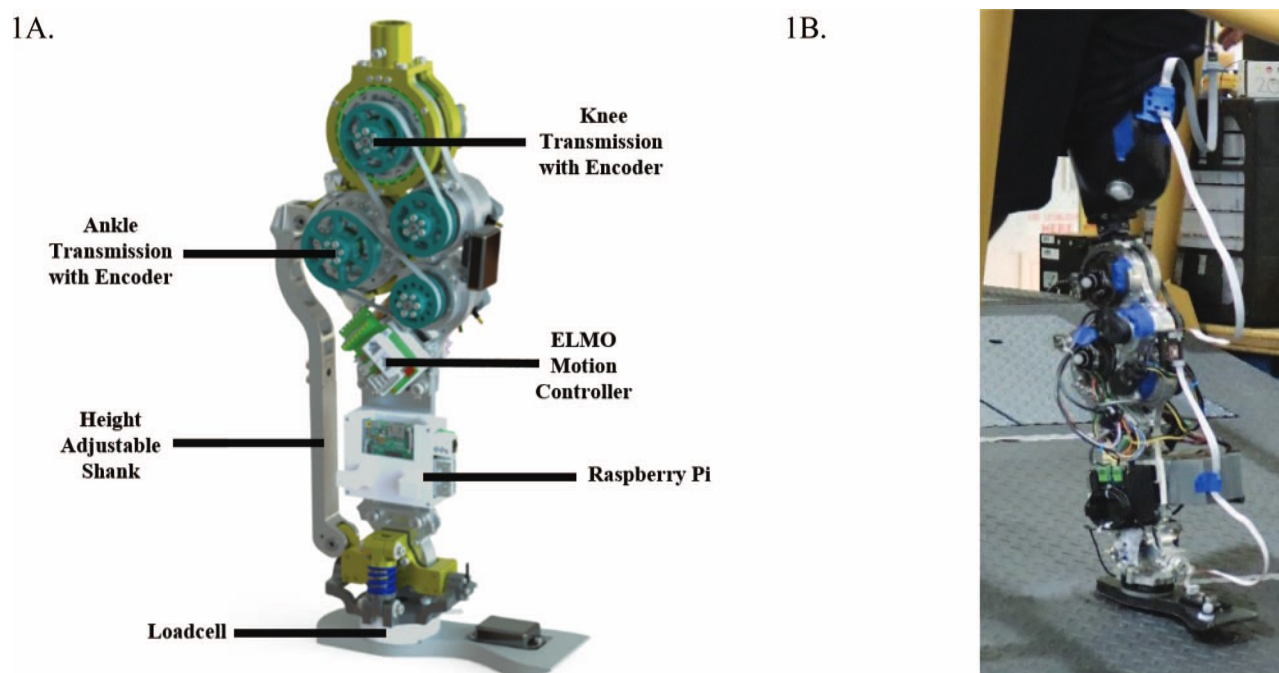


FIGURE 1. (A) Features of the device including: knee transmission with encoder (top right), ankle transmission with encoder (top left), ELMO motion controller (middle right), microprocessor (middle right), height-adjustable shank (middle left), and 6-DOF load cell (bottom left). (B) User walking with a prosthetic device on a ramp.

project, we defined success as a prosthesis that could (1) correctly recognize the different phases of gait, (2) tune joint impedance to scale across a range of gait speeds/inclination angles, and (3) generate knee and ankle kinematics similar to individuals without transfemoral amputation.

METHODS

Powered Prosthetic Device

The investigators developed a new iteration of a previous device,³⁰ from a collaboration between the Exoskeleton and Prosthetic Intelligent Controls lab at Georgia Institute of Technology and the Advanced Mechanical Bipedal Experimental Robotics Lab at California Institute of Technology (Fig. 1). The device has one actuated degree-of-freedom (DOF) at the knee joint in the sagittal plane, and two DOFs at the ankle—a powered DOF in the sagittal plane and a passive DOF in the frontal plane. The device is approximately 7.5 kg including the battery, which is similar to the missing biological limb mass (i.e., 13% of body weight),³¹ and has adjustable build heights of 46–63 cm to accommodate different residual limb lengths. Both knee and ankle joints are actively controlled using two 206 W brushless DC motors (MOOG BN23), which are capable of achieving approximately 1 N-m peak torque. To mimic human biological torque capabilities, the device utilizes a gear transmission ratio of 1:175 at the ankle joint and 1:120 at the knee joint. The gearbox consists of a harmonic drive

(model CSG-17-100-2UH-LW, Harmonic Drive, Peabody, MA) that reaches a 1:100 reduction and a variable pulley-belt system that produces the remaining gear reductions for both joints. The mechanical properties of each joint have an estimated efficiency of 70% (Supplementary Table S1).³⁰ Our powered multi-joint prosthesis is unique because it allows for closed-loop torque control with the series-elastic actuators, passive frontal plane DOF, and serves as a good controls testbed for implementing different controllers.

A raspberry pi 3 model B microprocessor (4×ARM Cortex-A53, 1.2 GHz) acts as the hardware–software interface platform, where all signal data is measured and logged. Both knee and ankle joints feature an incremental encoder (US Digital E5) concentrically placed in series with the motor, which measures both joint angle and velocity and is controlled through a motion controller (gold solo whistle controller, model G-SOLWHI20/100SE, ELMO Motion Control Technologies, Petah Tikva, Israel) over Controller Area Network (CAN) bus. The raspberry pi also incorporates a 6-DOF load cell (SRI M3714C2) to measure ground reaction forces over CAN bus. The whole system is powered through a 10-cell (37 V), 3600 mAh Li-Po battery (Venom Power) and a portable power bank for the Raspberry Pi (Fig. 1). Device controls are programmed in C++ packages that operate on the robot operating system platform. An accompanying graphical user interface capable of relaying live signals was developed using Python packages.

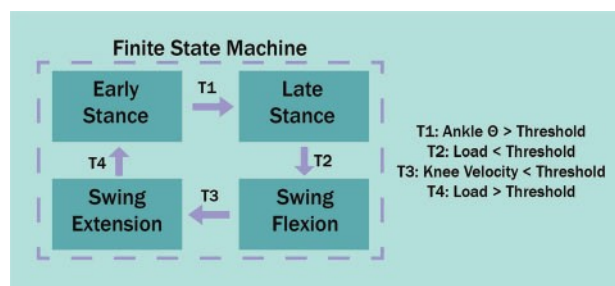


FIGURE 2. Demonstrates the finite state machine for a single ambulation mode, where the gait cycle is discretized into four states. T1 threshold was just a constant that had to be passed in order to transition. T2 and T4 were constants that represented % body weight of the user. T3 threshold was a constant multiplied by the peak knee velocity, where the constant was between 0 and 1. Each state had a unique set of virtual stiffness and damping (impedance) parameters for both the knee and ankle.

Control System

The investigators implemented a hierarchical control paradigm, featuring a high-, a mid-, and a low-level controller. The high-level controller uses machine learning and sensor fusion techniques to estimate user intent, environmental features and user state in real-time, and dynamically adapt to real-world environments. The low-level controller interfaces with the mid-level controller to ensure that the desired torque is actuated at each joint via series-elastic actuators and closed-loop feedback control. Both the high- and the low-level controllers are not a focus of this manuscript but can be seen in previous literature.^{20,32–34}

The prosthetic device utilized a mid-level impedance-based controller paired with a finite state machine that allowed for dynamic interaction between the user and environment.^{14,27,35,36} Thus, unlike a pure kinematic trajectory control approach, the system does not control user kinematics directly. The gait cycle is broken into discrete states (early/mid-stance, late stance, swing-phase flexion, and swing-phase extension), and in each state, a pair of impedance control laws govern the torque at the knee and ankle joints (Fig. 2).

The impedance controller models each joint as a virtual spring-damper system, where virtual spring stiffness (k), spring equilibrium angle (θ_e), and damping coefficient (b) can be adjusted to modify the desired torque of the joint (Eqn. 1).

$$\tau_{\text{desired}} = -k(\theta - \theta_e) - b\dot{\theta} \quad (1)$$

Transitions between states were carried out via a state machine that primarily used sets of thresholds based on mechanical sensors (i.e., encoders and 6-DOF load cell). These thresholds were adjustable by the experimenters to accommodate different gait patterns. The pairing of the finite state machine and the impedance controller allowed for power generation at key moments in the gait cycle, such as powered plantar flexion during push-off, powered knee flexion swing

initiation, powered knee swing extension assistance, and stiffening of the knee and ankle for braking during early-to mid-stance. Additionally, three modes of ambulation were implemented (level-ground walking, ramp ascent (RA), and ramp descent (RD)), each with a unique finite state machine. The investigators implemented scaling equations into the finite state machine to smooth transitions between states and reduce the number of independently tuned parameters. The rationale for implementing these equations can be found in previous work.⁸ Before any tuning was performed, an input of the user's body mass was required to use some of the following equations. The first scaling equation (Eqn. 2) modulated the ankle stiffness as a function of ankle angle and body weight based on previous studies that have rigorously determined ankle impedance as a function of the ankle in able-bodied subjects.³⁷ The second equation (Eqn. 3) scaled an impedance parameter from a specified starting value (p_{start}) to a specified final value (p_{final}) as a function of the vertical load on the prosthesis. This equation allowed for smooth transitioning of impedance parameters as the weight was removed from the prosthesis. The last scaling equation (Eqn. 4) altered knee equilibrium angle as a function of the knee angle, which is useful for providing smooth resistance during the ramp decline mode.⁸

$$k_{\text{ankle}} = \text{BM} \times (0.237 \times \theta_{\text{ankle}} + 0.028) \quad (2)$$

$$p = \frac{F_{\text{vertical}}}{\text{BM}} \times (p_{\text{start}} - p_{\text{final}}) + p_{\text{final}} \quad (3)$$

$$\theta_{e,\text{knee}} = C \times \theta_{\text{knee}} \quad (4)$$

Experimental Design

Six individuals (5 male and 1 female) with unilateral transfemoral amputation were recruited and provided informed consent according to the Georgia Institute of Technology Institutional Review Board (Protocol H16351: User-Independent Intent Recognition on a Powered Transfemoral Prosthesis; Supplementary Table S2).

The shank height of the device was adjusted to align the knee center of rotation of the prosthesis with the patient's biological knee center. The device was fitted and aligned by a certified prosthetist and the patient walked in a set of parallel bars over the ground while learning how to utilize powered assistance. Control parameters and prosthetic alignment were tuned and observed during this time to ensure the comfortable transfer of power during walking and minimization of clinical gait deviations. This adjustment period typically took 30–45 minutes per subject. In total, there are 28 parameters that can be adjusted per ambulation mode to modify the gait dynamics. Two experimental protocols were conducted after the initial tuning session, three participants (TF01, TF02, and TF03) performed level walking (LW) on a treadmill and four participants (TF02, TF04, TF05, and TF06) performed

a “ramp circuit.” The treadmill protocol consisted of having users walk at six different steady-state speeds: 0.63, 0.72, 0.80, 0.89, 0.98, and 1.07 m/s, respectively. This range of speed was adjusted to ensure that all subjects were able to finish all the trials. Each subject walked for 1 minute in each of the six conditions. The ramp circuit involved starting in standing mode, taking a LW step(s), transitioning to RA, ascending a 5-m ramp, transitioning back to LW, transitioning to RD, descending a 5-m ramp, and finally transitioning back to LW. Five different presets were tested, the inclination angles were 7.8°, 9.2°, 11.0°, 12.4°, and 14.0°, respectively. An additional pilot study was conducted where one participant (TF02) was asked to walk with his respective passive leg (C-Leg with Triton Vertical Shock (VS) foot) in LW, and RA/descent at $\pm 7.5^\circ$ on a treadmill for 1 minute in each condition. VICON motion capture analysis was performed to generate the kinematics seen in both the knee and ankle joints of the passive leg.

Data Analysis

The investigators analyzed the biomechanics of walking using the outputs from sensors in the prosthesis. Each gait cycle was parsed using our finite-state machine with MATLAB. Ten gait cycles per participant and per condition were normalized to 100 data points to facilitate inter-subject comparisons. Outcome measures included joint kinematics and accuracy of the state machine in recognizing phase changes. A similar process was also performed for the ramp circuits by extracting out RA and RD gait cycles.

Joint kinematics were qualitatively compared to previously published results on people without amputation.^{38,39} A repeated-measures analysis of variance was used to determine if there is a difference in the kinematic response between different walking speeds on the treadmill or incline/decline conditions on the ramp. Mauchly's Test of Sphericity tested variance across the conditions. When sphericity was violated, a Greenhouse–Geisser adjustment was applied. Kinematic outcome measures tested were peak knee flexion angle during swing, peak dorsiflexion angle in stance, and peak plantarflexion angle in push-off. To define the risk of type II error skewing the results due to the small sample size, observed power was calculated as $1 - \beta$. An impedance parameter analysis was also performed to provide a recommended table of how the impedance parameters should be implemented across different ambulation modes.

RESULTS

Tuning Parameters

In LW, the three main parameters tuned included the ankle equilibrium angle in late stance, adjusting the transition threshold from early stance to late stance (T1) as well as from late stance to swing flexion (T2). In RA, only two unique parameters were adjusted that included the stiffness

and damping of the knee joint in swing extension. In RD, two unique parameters, the stiffness, and damping in early stance were altered. Scaling equations (Eqs 2, 3, and 4) were utilized to adjust parameters with respect to kinematic and kinetic variables to ensure smoother gait.

The controller was able to robustly recognize the different phases of gait with no errors. The participants (TF01–TF03) took 265 strides, 265 strides, and 218 strides respectively during walking on the treadmill. This resulted in a total of 748 prosthesis steps that created 2992 phase transitions in the first experiment. In sloped walking, each individual took between 100 and 150 strides across all inclination angles resulting in a total of 839 steady-state prosthesis steps overall that produced a combined 3356 phases transitions during the ramp circuits. In total, there were 748 LW strides, 368 RA strides, and 471 RD strides with a total of 6348 phase transitions. In all cases, the state machine correctly recognized each part of the gait cycle (heel contact, mid-stance, toe-off, and early-to-mid swing) and altered joint impedance parameters accordingly. In terms of setting the transitional triggers, only two triggers required tuning during LW and these propagated to the ramp modes (Table 1).

Kinematics across Walking Speeds

The average knee angle remained extended during the stance portion of the gait phase (Fig. 3). Neither the knee flexion angle during swing ($p = 0.349, 1 - \beta = 0.151$), the plantarflexion angle during push-off ($p = 0.101, 1 - \beta = 0.412$), or the maximum dorsiflexion angle ($p = 0.902, 1 - \beta = 0.055$) changed as a function of walking speed on the treadmill. All subjects were able to walk at the range of 0.63–1.07 m/s on the treadmill without changing impedance parameters in the state machine.

Kinematics across Ambulation Modes

The impedance controller was able to generate walking gait that was comparable to able-bodied kinematics in many aspects but with a notable set of exceptions (Fig. 4). At the knee, the powered prosthesis did not provide stance phase knee flexion in any of the three modes but did allow for the user to have controlled knee flexion during RD. Swing phase closely matched able-bodied data in LW and RA, but additional swing flexion was not provided for RD. At the ankle, both controlled dorsiflexion and active powered plantarflexion were rendered during stance phase but were not as exaggerated in terms of ankle angle compared to the able-bodied subjects.

Kinematics across Inclination Angles

Both joint angles produced similar trajectories across inclination angles (Fig. 5). Neither the knee flexion angle during swing ($p = 0.283, 1 - \beta = 0.213$), the plantar flexion angle during push-off ($p = 0.337, 1 - \beta = 0.172$), or the maximum

TABLE 1. The final set of impedance parameters across participants for LW, RA, and RD

Mode	Phase	Ankle Parameters			Knee Parameters			Trigger Thresholds			
		k (Nm/deg)	b (Nms/deg)	θ (deg)	k (Nm/deg)	b (Nms/deg)	θ (deg)	T1 (deg)	T2 (% F _{vertical})	T3 (deg/s)	T2 (% F _{vertical})
Level Walking	Early Stance	EQ2	0.25	0	3	0.1	0				
	Late Stance	EQ2	0.1	EQ3: p _{start} = 0 p _{final} = -17 to -23	EQ3: p _{start} = 3 p _{final} = 1	0.05	EQ3: p _{start} = 0 p _{final} = 63	5.0 - 6.0	20.0 - 25.0	0.3	50
	Swing Flexion	2.6	0.1	1.75	1.4	0.1	63				
	Swing Extension	2.1	0.525	1.75	1.4	0.2	0				
	Early Stance	EQ2	0.25	0	3	0.15	0				
Ramp Ascent	Late Stance	EQ2	0.1	Same as LW	EQ3: p _{start} = 3 p _{final} = 1	0.15	EQ3: p _{start} = 0 p _{final} = 63	6.5	Same as LW	0.4	50
	Swing Flexion	2.6	0.1	1.75	1.4	0.1	63				
	Swing Extension	2.1	0.525	1.75	1.6 [1.4 to 2.0]	.20 [.15 to .25]	0				
	Early Stance	3.5	0.25	0	2	.45 [.4 to .5]	EQ4 [.8 to .97]				
Ramp Descent	Late Stance	2.5	0.1	EQ3: p _{start} = 0 p _{final} = -11.5	EQ3: p _{start} = 2 p _{final} = 1	Previous Value	EQ3: p _{start} = Previous value p _{final} = 25	Same as LW	Same as LW	0.3	40
	Swing Flexion	2.4	0.1	3	1.2	0.1	45				
	Swing Extension	2.4	0.1	3	2	0.15	0				

Note. Green highlights the subject-specific tuning parameters. Baseline values and the associated tuning range in brackets are displayed for each green highlight.

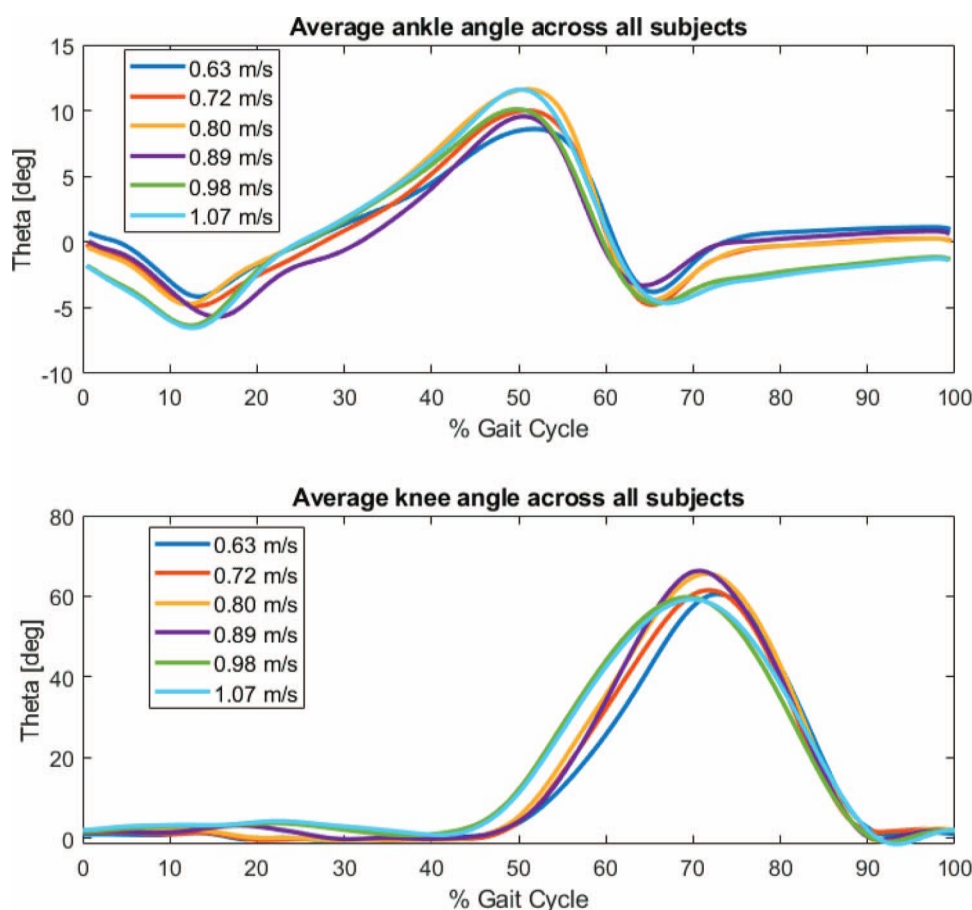


FIGURE 3. Average kinematic profiles of both ankle and knee joint during LW on a treadmill ($N = 3$) across different walking speeds.

dorsiflexion angle ($p = 0.279$, $1 - \beta = 0.201$) significantly changed as a function of ground incline angle on the ramp. All subjects were able to ascend the ramp between the range of 7.8° and 14.0° without changing impedance parameters in the RA mode.

Both joint angles produced similar trajectories across different decline angles (Fig. 6). Neither the knee flexion angle during swing ($p = 0.673$, $1 - \beta = 0.084$), the plantarflexion angle during push-off ($p = 0.461$, $1 - \beta = 0.106$), or the maximum dorsiflexion angle ($p = 0.3$, $1 - \beta = 0.156$) significantly changed as a function of ground decline angle on the ramp. All subjects were able to descend the ramp between the range of 7.8 – 14.0° without changing impedance parameters in the RD mode.

DISCUSSION

In this study, the investigators developed a powered knee and ankle prosthesis with a controller that could recognize the different phases of gait, tune joint impedance across a range of gait speeds/inclination angles, and generate knee and ankle kinematics similar to individuals without

amputation. The controller correctly recognized 6348 phase transitions across both walking speeds and inclination angles demonstrating the ability to render correct transitions to ensure reliable gait. The state machine's ability to correctly identify the phase of gait and set joint impedance parameters accordingly demonstrates its ability to assist users to ambulate over different conditions in a safe, seamless, and natural manner.

The tuning performed while the participant walked in the parallel bars was sufficient to obtain steady-state LW. There were seven unique parameters tuned across all ambulation modes (Table 1) that the investigators found useful for patient-specific accommodation. The final equilibrium angle of the ankle was tuned during late stance phase to improve push-off mechanics. There was some variance in the magnitude of tuned push-off preferred by the subjects, which was accommodated for using this parameter. The transition between early stance and late stance (T1) was tuned to ensure late stance was triggered by setting an ankle angle threshold. This setting was personalized for all subjects. The experimenters also found it useful to adjust the timing of the transition from late stance to swing flexion phase (T2). This parameter effectively controlled the speed of the swing-phase initiation.

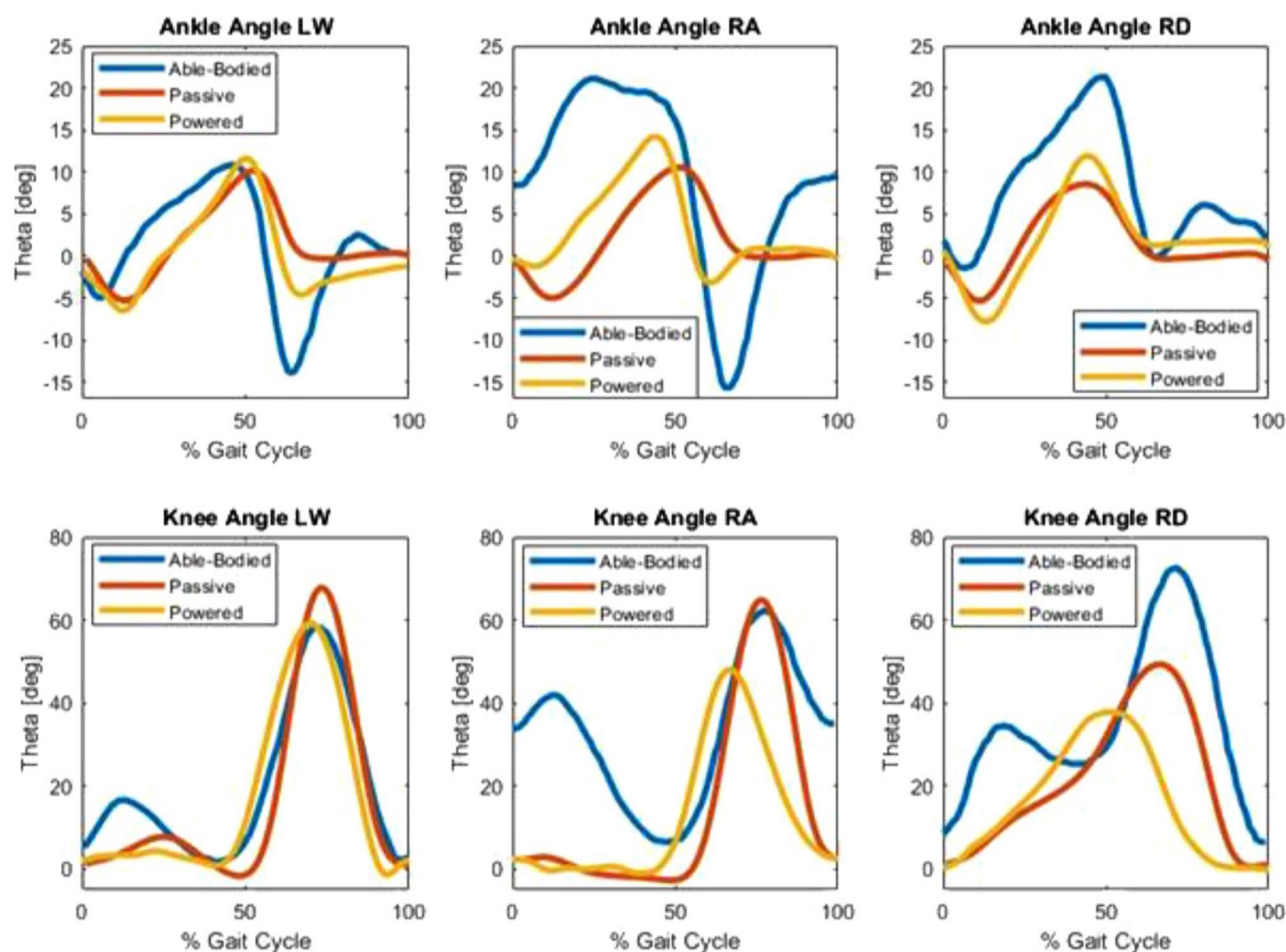


FIGURE 4. Kinematic profiles of both ankle and knee joint in 3 different ambulation modes: LW ($N = 3$), RA ($N = 4$), and RD ($N = 4$) comparing between healthy individuals ($N = 40$), and our powered prosthesis. Able-bodied LW and ramp kinematic profiles were found in previous literature.^{38,39} Passive data is from a pilot study conducted for LW, RA/RD at $\pm 7.5^\circ$.

In RA, the stiffness and damping were modified to control the acceleration of knee extension during the swing extension phase. In RD, two impedance parameters (knee damping and equilibrium angle) were tuned to maximize subject comfort. Of all the impedance parameters, the subject comfort was most sensitive to the RD settings during early stance phase at the knee.

Few parameters are necessary to clinically tune the prosthesis. This is in contrast to prior criticisms of impedance-based controllers.^{21,23,40} This is likely due to the pairing of an impedance-based controller with a finite state machine, and the translatability of impedance settings seen in previous literature and used on a different prosthesis design.⁸ This combination produced a fairly simple and intuitive methodology that enabled our clinicians to quickly tune the prosthesis and will facilitate future clinical translation. The tuning process may be improved further through integration with machine learning.

The lack of statistical differences across speeds or ramps for the kinematic variables were associated with low

statistical power, indicating the sample size was insufficient to draw definitive conclusions how prosthetic knee and ankle kinematics vary on across speeds. Future research with more subjects may be able to better distinguish the finer details of how the prosthesis is performing across speeds. Therefore, this discussion will focus on the qualitative aspects of the knee and ankle kinematics compared to published data on people with intact limbs.

Knee and ankle kinematics closely followed able-bodied data during LW, regardless of speed, with a peak knee flexion angle of $\sim 60^\circ$ during swing flexion (Fig. 3). The initial knee flexion typically seen during able-bodied gait was not demonstrated in these subjects (Fig. 3). Initial knee flexion was induced during the tuning sessions; however, participants reported feeling less comfortable and would not tolerate this feature. Therefore, the knee flexion during early stance phase, normally seen in able-bodied gait (Figs 3 and 4), was tuned out of the device to maximize patient comfort as the device would be used in clinical practice. The subjects may not have preferred to have the knee flex during stance phase due to

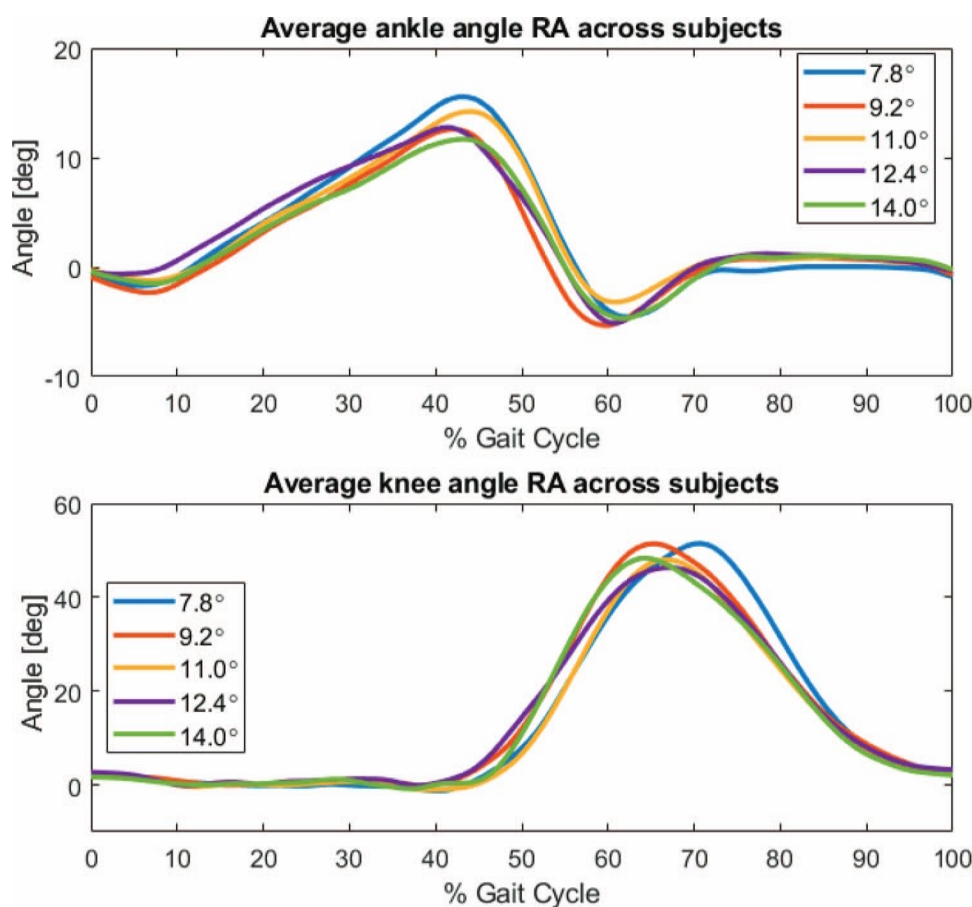


FIGURE 5. Average kinematic profiles of both ankle and knee joint in RA at five different inclination angles ($N = 4$).

motion inheritance in the limb/socket interface that would enable impact absorption to occur between the residual limb and the prosthetic socket, energy absorption normally handled by knee flexion. Alternatively, the users did not employ knee flexion strategies during stance in their own prostheses and, therefore, were not trained to use it in our prosthesis. Furthermore, the powered prosthesis exhibited powered ankle plantar flexion compared to the passive device during push-off in all ambulation modes, whereas the powered knee kinematics only matched in LW.

For RA, both the knee and ankle joints exhibited similar patterns across different inclination angles. For RD, the knee flexion tuning parameters were modulated based on user preference to ensure smooth transitions between stance and swing phase and allow the user to leverage the support provided by the high knee joint impedance and “ride” the prosthesis down during downhill walking. Future research, with more subjects, will be able to explore the details on how this controller is adapting to specific inclination angles.

Our study shows how our powered prosthesis is able to render similar kinematics to able-bodied individuals at normal and slow speeds but lacks the ability to compare to speeds in a higher range. For reference, healthy individuals’ average

preferred gait speed is approximately 1.4 m/s and transfemoral subjects’ self-selected speed is approximately 1.2 m/s.^{41,42} Even though our powered knee and ankle prosthesis provides more power compared to a passive prosthesis (Fig. 4), the increased mass and bulk compared to commercially available prostheses can still cause users to utilize their sound side more or use other compensatory movements when ambulating in different modes. As new technology emerges, weight and cost must be important considerations for building the future generation of robotic powered prostheses in order for them to be considered as viable options.

Future work that compares our powered knee-ankle prosthesis against the subject’s personal passive prosthesis will allow us to understand the biomechanical differences between the sound versus the amputated side, and determine if common clinical outcome measures are met. Furthermore, a deeper understanding of how dual-powered prostheses compare against single-joint commercially available prostheses may be essential to disseminate this technology. This would allow us to understand whether there are differences between using two powered joints in synchrony versus putting two independently controlled powered joints “together.”

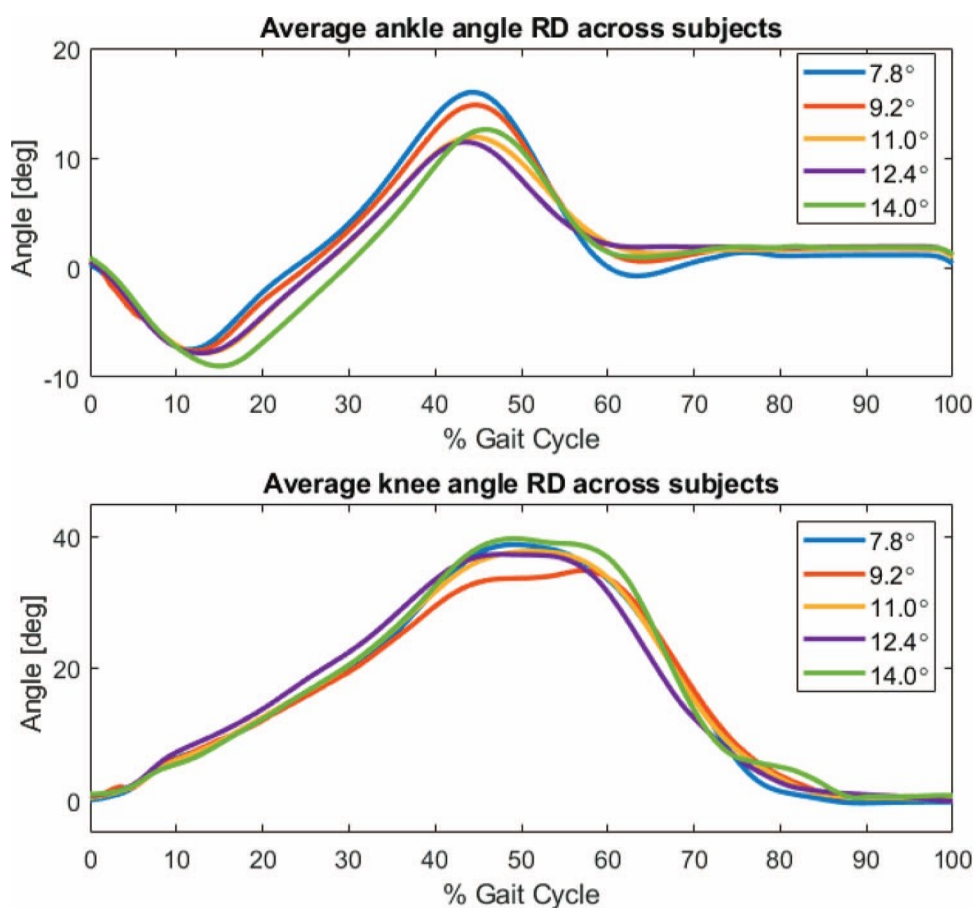


FIGURE 6. Average kinematic profiles of both ankle and knee joint in RD at five different inclination angles ($N = 4$).

CONCLUSION

This new powered knee and ankle prosthesis generated reliable walking gait across ambulation modes. The control system was able to correctly and robustly identify the phase of gait, set gait phase-specific impedance, and generate near-normal lower-limb kinematics using the minimal tuning of impedance parameters (7 out of 84). This controller was also capable of scaling powered assistance to the user across a range of walking speeds and inclination grades, which is a step toward being able to restore functionality lost through amputation.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *MILMED* online.

ACKNOWLEDGMENTS

The authors acknowledge Aaron Ames and Eric Ambrose from the AMBER Lab at CalTech for their contributions on the mechanical design of the prosthetic device. The investigators thank Kinsey Herrin with the Georgia Tech MSPO program for patient fitting and guidance on device improvements as well as some undergraduate students (Jared Li, Alice Bok, and Noah Cho) who helped with data collection and analysis. The work was supported, in part, by a Fulbright fellowship awarded to Jonathan Camargo-Levy. I have obtained written permission from all persons named in the Acknowledgments.

FUNDING

This work was funded by Department of Defense Congressionally Directed Medical Research Programs (DoD CDMRP) Award No. W81XWH-17-1-0031. This work was supported by the Office of the Assistant Secretary of Defense for Health Affairs through the Orthotics and Prosthetics Outcomes Research Program Prosthetics Outcomes Research Award under Award No. W81XWH-17-1-0031.

REFERENCES

1. Ingraham KA, Fey NP, Simon AM, Hargrove JL: Assessing the relative contributions of active ankle and knee assistance to the walking mechanics of transfemoral amputees using a powered prosthesis. *PLoS One*; 2016; 11(1): e0147661.
2. Highsmith MJ, Goff LM, Lewandowski AL, et al: Low back pain in persons with lower extremity amputation: a systematic review of the literature. *Spine J*; 2019; 19(3): 552–63.
3. Bellmann M, Schmalz T, Blumentritt S: Comparative biomechanical analysis of current microprocessor-controlled prosthetic knee joints. *Arch Phys Med Rehabil*; 2010; 91(4): 644–52.
4. Thiele J, Westebbe B, Bellmann M, Kraft M: Designs and performance of microprocessor-controlled knee joints. *Biomed Tech Eng*; 2014; 59(1): 65–77.
5. Nolan L, Lees A: The functional demands on the intact limb during walking for active transfemoral and transtibial amputees. *Prosthet Orthot Int*; 2000; 24(2): 117–25.
6. Gailey R: Review of secondary physical conditions associated with lower-limb amputation and long-term prosthesis use. *Artic J Rehabil Res Dev*; 2008; 45(1): 15–30.

7. Morgenroth DC, Roland M, Pruziner AL, Czerniecki JM: Transfemoral amputee intact limb loading and compensatory gait mechanics during down slope ambulation and the effect of prosthetic knee mechanisms. *Clin Biomech*; 2018; 55: 65–72.
8. Simon AM, Ingraham KA, Fey NP, et al: Configuring a powered knee and ankle prosthesis for transfemoral amputees within five specific ambulation modes. *PLoS One*; 2014; 9(6): e99387.
9. Fey NP, Simon AM, Young AJ, Hargrove LJ: Controlling knee swing initiation and ankle plantarflexion with an active prosthesis on level and inclined surfaces at variable walking speeds. *IEEE J Transl Eng Heal Med*; 2014; 2: 1–12.
10. Young A, Simon A, Hargrove L: A training method for locomotion mode prediction using powered lower limb prostheses. *IEEE Trans Neural Syst Rehabil Eng*; 2014; 22(3): 671–7.
11. Rouse EJ, Mooney LM, Herr HM: Clutchable series-elastic actuator: implications for prosthetic knee design. *Int J Rob Res*; 2014; 33(13): 1611–25.
12. Hoover CD, Fulk GD, Fite KB: The design and initial experimental validation of an active myoelectric transfemoral prosthesis. *J Med Device*; 2012; 6(1): 011005.
13. Azocar AF, Member S, Mooney LM, Hargrove LJ, Rouse EJ: Design and characterization of an open-source robotic leg prosthesis. In: 2018 7th IEEE International Conference on Biomedical Robotics and Biomechanics (Biorob); 2018:111–8.
14. Lawson BE, Mitchell J, Truex D, Shultz A, Ledoux E, Goldfarb M: A robotic leg prosthesis: design, control, and implementation. *IEEE Robot Autom Mag*; 2014; 21(4): 70–81.
15. Lambrecht BGA, Kazerooni H: Design of a semi-active knee prosthesis. In: 2009 IEEE International Conference on Robotics and Automation. IEEE; 2009: 639–45.
16. Lenzi T, Sensinger J, Lipsey J, Hargrove L, Kuiken T: Design and preliminary testing of the RIC hybrid knee prosthesis. In: 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE; 2015:1683–6.
17. Cempini M, Hargrove LJ, Lenzi T: Design, development, and bench-top testing of a powered polycentric ankle prosthesis. In: 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems; 2017: 1064–9.
18. Jimenez-Fabian R, Verlinden O: Review of control algorithms for robotic ankle systems in lower-limb orthoses, prostheses, and exoskeletons. *Med Eng Phys*; 2012; 34(4): 397–408.
19. Goldfarb M, Lawson B, Shultz A: Realizing the promise of robotic leg prostheses. *Sci Transl Med*; 2013; 5(210):r 210ps15.
20. Varol HA, Sup F, Goldfarb M: Multiclass real-time intent recognition of a powered lower limb prosthesis. *IEEE Trans Biomed Eng*; 2010; 57(3): 542–51.
21. Gregg RD, Lenzi T, Hargrove LJ, Sensinger JW: Virtual constraint control of a powered prosthetic leg: from simulation to experiments with transfemoral amputees. *IEEE Trans Robot*; 2014; 30(6): 1455–71.
22. Holgate MA, Sugar TG, Böhler AW: A novel control algorithm for wearable robotics using phase plane invariants. In: 2009 IEEE International Conference on Robotics and Automation. IEEE; 2009: 3845–50. Available at <https://ieeexplore.ieee.org/abstract/document/5152565>; accessed February 3, 2019.
23. Huang H, Crouch DL, Liu M, Sawicki GS, Wang D: A cyber expert system for auto-tuning powered prosthesis impedance control parameters. *Ann Biomed Eng*; 2016; 44(5): 1613–24.
24. Lenzi T, Hargrove LJ, Sensinger JW: Minimum jerk swing control allows variable cadence in powered transfemoral prostheses. In: 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE; 2014:2492–95. Available at <https://ieeexplore.ieee.org/document/6944128>; accessed February 13, 2019.
25. Quintero D, Villarreal DJ, Lambert DJ, Kapp S, Gregg RD: Continuous-phase control of a powered knee-ankle prosthesis: amputee experiments across speeds and inclines. *IEEE Trans Robot*; 2018; 1–16.
26. Ledoux ED, Goldfarb M: Control and evaluation of a powered transfemoral prosthesis for stair ascent. *IEEE Trans Neural Syst Rehabil Eng*; 2017; 25(7): 917–24.
27. Sup F, Bohara A, Goldfarb M: Design and control of a powered transfemoral prosthesis. *Int J Rob Res*; 2008; 27(2): 263–73.
28. Hogan N: Impedance Control - an approach to manipulation part II - implementation. *J. Dyn Syst Meas Control*; 1985; 107(1): 1–7.
29. Shepherd MK, Rouse EJ: The VSPA foot: a quasi-passive ankle-foot prosthesis with continuously variable stiffness. *IEEE Trans Neural Syst Rehabil Eng*; 2017; 25(12): 2375–86.
30. Zhao H, Ambrose E, Ames AD: Preliminary results on energy efficient 3D prosthetic walking with a powered compliant transfemoral prosthesis. In: 2017 IEEE International Conference on Robotics and Automation; 2017:1140–7. Available at <https://ieeexplore.ieee.org/document/7989136>; accessed February 13, 2019.
31. Clauser CE, McConville JT, Young JW: Weight, volume, and center of mass of segments of the human body, 1969. <https://apps.dtic.mil/dtic/tr/fulltext/u2/710622.pdf>.
32. Young AJ, Simon AM, Fey NP, Hargrove LJ: Intent recognition in apowered lower limb prosthesis using time history information. *Ann Biomed Eng*; 2013; 42(3): 631–41.
33. Young AJ, Smith LH, Rouse EJ, Hargrove LJ: A comparison of the real-time controllability of pattern recognition to conventional myoelectric control for discrete and simultaneous movements. *J Neuroeng Rehabil*; 2014; 11: 5.
34. Spanias JA, Simon AM, Finucane SB, Perreault EJ, Hargrove LJ: Online adaptive neural control of a robotic lower limb prosthesis. *J Neural Eng*; 2018; 15(1): 016015.
35. Liu M, Zhang F, Datsis P, Huang H: Improving finite state impedance control of active-transfemoral prosthesis using dempster-shafer based state transition rules. *J Intell Robot Syst Theory Appl*; 2014; 76(3–4): 461–74.
36. Hogan N: Impedance control: an approach to manipulation: part II—implementation. *J Dyn Syst Meas Control*; 1985; 107(1): 8–16.
37. Rouse E, Hargrove L, Perreault E, Kuiken T: Estimation of Human Ankle Impedance During Walking Using the Perturbator Robot. In: Proceedings of the 4th IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechanics. Rome, Italy; 2012. Available at <https://ieeexplore.ieee.org/document/6290842>; accessed February 13, 2019.
38. Kadaba MP, Ramakrishnan HK, Wootten ME: Measurement of lower extremity kinematics during level walking. *J Orthop Res*; 1990; 8(3): 383–92.
39. McIntosh AS, Beatty KT, Dwan LN, Vickers DR: Gait dynamics on an inclined walkway. *J Biomech*; 2006; 39(13): 2491–502.
40. Wen Y, Si J, Gao X, Huang S, Huang HH, Member S: A new powered lower limb prosthesis control framework based on adaptive dynamic programming. *IEEE Trans Neural Networks Learn Syst*; 2016: 1–6. Available at <https://ieeexplore.ieee.org/document/7508991> accessed February 13, 2019.
41. Bohannon RW: Comfortable and maximum reference values and determinants. Age and comfortable and maximum walking speed of adults aged 20–79 years: reference values and determinants. *Age and Ageing*; 1997; 15–9.
42. Lamoth CJC, Ainsworth E, Polonski W, Houdijk H: Variability and stability analysis of walking of transfemoral amputees. *Med Eng Phys*; 2010; 1009–14.

Appendix B: IEEE Robotics and Automation Letters Journal Paper

Title: Machine Learning Model Comparisons of User Independent & Dependent Intent
Recognition Systems for Powered Prostheses

Authors: Krishan Bhakta, Jonathan Camargo, Luke Donovan, Kinsey Herrin, and Aaron Young

Date of Publication: July 7, 2020

Machine Learning Model Comparisons of User Independent & Dependent Intent Recognition Systems for Powered Prostheses

Krishan Bhakta¹, Jonathan Camargo¹, *Student Member, IEEE*, Luke Donovan, Kinsey Herrin²,
and Aaron Young³, *Member, IEEE*

Abstract—Developing intelligent prosthetic controllers to recognize user intent across users is a challenge. Machine learning algorithms present an opportunity to develop methods for predicting user's locomotion mode. Currently, linear discriminant analysis (LDA) offers the standard solution in the state-of-the-art for subject dependent models and has been used in the development of subject independent applications. However, the performance of subject independent models differ radically from their dependent counterpart. Furthermore, most of the studies limit the evaluation to a fixed terrain with individual stair height and ramp inclination. In this study, we investigated the use of the XGBoost algorithm for developing a subject independent model across 8 individuals with transfemoral amputation. We evaluated the performance of XGBoost across different stair heights and inclination angles and found that it generalizes well across preset conditions. Our findings suggest that XGBoost offers a potential benefit for both subject independent and subject dependent algorithms outperforming LDA and NN (DEP SS Error: $2.93\% \pm 0.49\%$, DEP TS Error: $7.03\% \pm 0.74\%$, IND SS Error: $10.12\% \pm 3.16\%$, and IND TS Error: $15.78\% \pm 2.39\%$) ($p < 0.05$). We were also able to show that with the inclusion of extra sensors the model performance could continually be improved in both user dependent and independent models ($p < 0.05$). Our study provides valuable information for future intent recognition systems to make them more reliable across different users and common community ambulation modes.

Index Terms—Prosthetics and exoskeletons, wearable robots, human performance augmentation, mode classification, transfemoral amputation.

I. INTRODUCTION

OVER the last two decades there have been many advancements in powered prosthetic technology that can aid users with lower-limb amputation and restore their locomotive abilities [1]–[3]. However, best practices for effectively coupling powered prostheses to individual users remain elusive. A recent challenge in creating smarter controllers is understanding how to recognize and adapt to user intent. Controllers which seamlessly decipher user intent and provide appropriate assistance will have greater viability in clinical scenarios.

Recent projections indicate that the number of individuals with lower-limb loss will increase significantly over the next several decades [4]. The steady increase of lower-limb amputations warrants the need to develop more advanced technology to allow users to ambulate more naturally and over terrains that they would often encounter in the community, such as stairs and ramps. Current solutions are mainly passive, which lack the ability to generate net positive work over a gait cycle. Hence, users develop compensatory strategies to walk which include having higher intact limb-joint moments that may lead to joint degradation, pain, and osteoarthritis [5]–[8]. Powered prostheses may help to reduce some of these compensatory strategies, but still require more advanced and reliable controller designs [9].

Recent advances on the integration of microprocessors, microcontrollers, sensors, and actuators coupled with innovative mechanical design have paved the way toward further advancing smarter prosthetic technology. These powered devices show promise in being able to help lower-limb amputees function at higher levels in their daily lives because of their ability to accommodate and provide appropriate assistance on different terrain which may in turn improve overall quality of life [10]. Robust and reliable implementation of controllers capable of accurate intent recognition (i.e. recognizing the desire to change between ambulation modes) is a non-trivial requirement given the high variability that frequently presents itself within given clinical populations.

Prosthetic control strategies have been explored to understand what techniques can be utilized to develop smarter algorithms [11]. Many research groups have focused on single

Manuscript received February 24, 2020; accepted June 16, 2020. Date of publication July 7, 2020; date of current version July 16, 2020. This letter was recommended for publication by Associate Editor E. Rouse and Editor P. Valdastrì upon evaluation of the reviewers' comments. This work was supported in part by the Fulbright fellowship awarded to Jonathan Camargo-Levy and in part by the Office of the Assistant Secretary of Defense for Health Affairs, through the Orthotics and Prosthetics Outcomes Research Program Prosthetics Outcomes Research Award under Award No. W81XWH-17-1-0031. Opinions, interpretations, conclusions and recommendations are those of the author and are not necessarily endorsed by the Department of Defense. (*Corresponding author: Krishan Bhakta.*)

Krishan Bhakta is with the Exoskeleton and Intelligent Controls (EPIC) Lab, Atlanta, GA 30332 USA, and also with the Woodruff School of Mechanical Engineering, Georgia Institute of Technology, Atlanta, GA 30332 USA (e-mail: kbbhakta3@gatech.edu).

Jonathan Camargo, Kinsey Herrin, and Aaron Young are with the Exoskeleton and Intelligent Controls (EPIC) Lab, Atlanta, GA 30332 USA, with the Woodruff School of Mechanical Engineering, Georgia Institute of Technology, Atlanta, GA 30332 USA, and also with the Institute for Robotics and Intelligent Machines, Georgia Institute of Technology, Atlanta, GA 30332 USA (e-mail: jon-cama@gatech.edu; kinsey.herrin@gatech.edu; aaron.young@me.gatech.edu).

Luke Donovan is with the School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA 30332 USA, and also with the Exoskeleton and Intelligent Controls (EPIC) Lab, Atlanta, GA 30332 USA (e-mail: ldonovan7@gatech.edu).

This letter has supplementary downloadable material available at <https://ieeexplore.ieee.org>, provided by the authors.

Digital Object Identifier 10.1109/LRA.2020.3007480

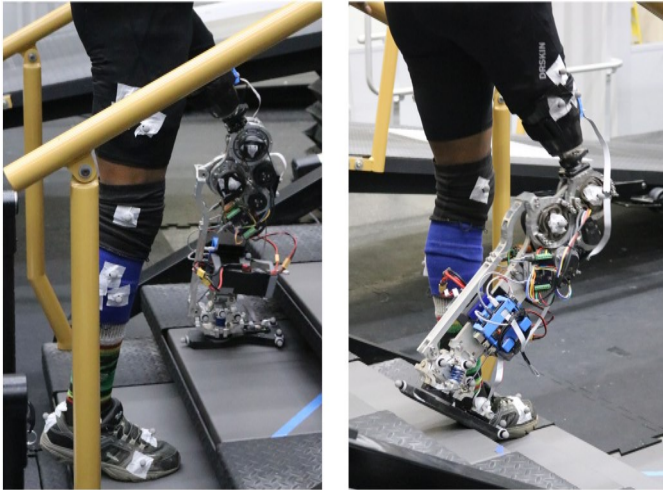


Fig. 1. Experimental setting in which one individual with transfemoral amputation is completing a stair ambulation trial across our custom-built terrain park. The terrain park is adjustable and can be modified between different stair heights and inclination angles. Embedded sensors on the prosthesis which include two joint encoders, one 6-DOF load cell, and three 6-axis inertial measurement units are useful in deciphering user intent.

lower-limb joint devices, and the lower limb prosthetic market to date only includes single joint (knee or ankle) powered technology [12], [13]. However, when more than one biological joint is missing, such as in a transfemoral amputation, an additional challenge is to ensure that two independently powered prosthetic joints can be controlled in a synchronous and stable manner. The most common prosthetic control strategies typically employ a three-tier controller paradigm: high-level, mid-level and low-level control [11], [14].

The high-level controller is responsible for detecting and deciphering user intent (i.e. determining locomotion mode or estimating environmental variables). The mid-level controller generates a desired profile at each joint throughout the gait cycle using either torque or position laws. The low-level controller's responsibility is to ensure that the actual torque output from the motor and transmission matches the desired torque. The focus of this study was to enhance the high-level controller as it is critical that these predictions have high accuracy given their direct impact on the behavior of the other two tiers, triggering actions of the prosthesis that depend on ambulation mode. Hence, the complete response of the powered prosthesis heavily depends on the determination of the user's ambulation mode. Manual triggers to transition between different locomotion modes are non-intuitive and presents a cognitive burden to the user while walking.

Machine learning or pattern recognition techniques have been shown to classify the ambulation mode in powered prostheses from mechanical sensors [15]–[19] and neuromuscular signals [20]. These techniques have shown levels of accuracy that demonstrate potential for the application in intelligent control of detecting ambulation modes. Simon *et al.* implemented a mode-specific classifier that utilized a delayed mode transition

decision of 90 ms while achieving an error of less than 0.5% [21]. However, as has been demonstrated in stability and error recovery studies, the response of such a system is highly sensitive to classification errors [22]. Traditionally, these implementations use methods that are relatively simple such as linear discriminant analysis (LDA) based on Bayesian theory [16], [17], [23], [24]. This offers the advantage of ease of use and fast training but are limited in capturing complex data dependencies. In addition, most of the methods have been used in a subject dependent setting, where they require training for everyone that wears the device, failing to capture patterns that are generalized across different users. Overcoming this challenge could reduce the burden of gathering lots of training data and may facilitate the adoption of smarter prostheses. In a previous study we proposed one of the first attempts of a method to produce subject independent classification that reduced the error levels to a range that allowed its use to control a prosthetic device [24]. However, we consider that additional development is needed to improve such systems, in particular with respect to a limitation that is consistently found in the literature: which is that all the training data is collected on a single ramp grade/stair height and tested on the same conditions. Furthermore, in most prior studies, classification accuracy have only been reported for a single height/incline in the training set. For real-world applications, these methods do not adequately represent community ambulation which has a larger variation in terrain, and as such, an intent recognition system must have the capability of adapting to different stair heights and inclination angles. However, this is a much more complex problem for a machine learning algorithm and is still an under-explored area of research.

Recent results in machine learning literature show the practical advantage of the gradient tree boosting method in classification problems with tabular data in complex classification scenarios [25]–[29]. Amongst different implementations, the open source package XGBoost [30] has been established as a robust solution in a wide range of problems, dominating competitions such as Kaggle [31]. XGBoost is a supervised machine learning algorithm based on gradient boosting and ensemble learning techniques. This method allows representation of the learning problem as gradient descent on an arbitrary differentiable loss function. This technique uses clever penalization of individual trees by including an additional regularization term in the loss function to combat overfitting and to improve the classification or regression output compared to its predecessors. This algorithm was selected for multiple reasons which include: 1) additive tree models that can be seen to adaptively determine the size of local neighborhoods (i.e. improves the flexibility of the fit to the data), 2) weight functions are updated at each subsequent iteration of creating the tree while taking the bias-variance tradeoff into consideration during fitting, and 3) approximating complex functional relationships using additive tree models [25], [30], [32]. In addition, this model is easily usable and efficient when training on different tasks. This decision tree boosting algorithm also allows us not to be constrained with the assumptions of Bayesian classifiers in which a certain covariance structure is specified. In the realm of exoskeletons and prostheses, several

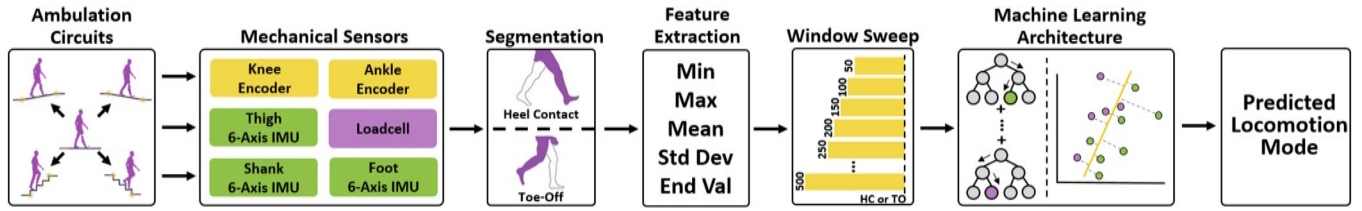


Fig. 2. The machine learning workflow used to predict user locomotion mode is shown. Users were asked to perform ambulation circuits which involved walking in 5 locomotion modes - LW, RA, RD, SA, and SD. Joint encoders that measured angular position and velocity, 6-DOF loadcell that measured ground reaction forces & moments, and IMUs that measured acceleration and rotational velocities were first segmented into two phases - heel contact and toe-off. The next algorithm consisted of transforming the data into several features (minimum, maximum, mean, standard deviation, and ending value) for a fixed window size. Next, a window size sweep was performed to find optimal window length to predict locomotion mode based on transitional error. The features were then passed through each machine learning algorithm (LDA, NN, and XGBoost) to predict locomotion mode. NN and XGBoost had to undergo an extra step of hyper-parameter tuning. In NN, layers, nodes, optimizer, learning rate, activation function, and batch size were swept. In XGBoost, learning rate, maximum tree depth, regularization term, and minimum gain were swept. After an optimized set of parameters were chosen, models were trained for our 6 different case studies to predict locomotion mode.

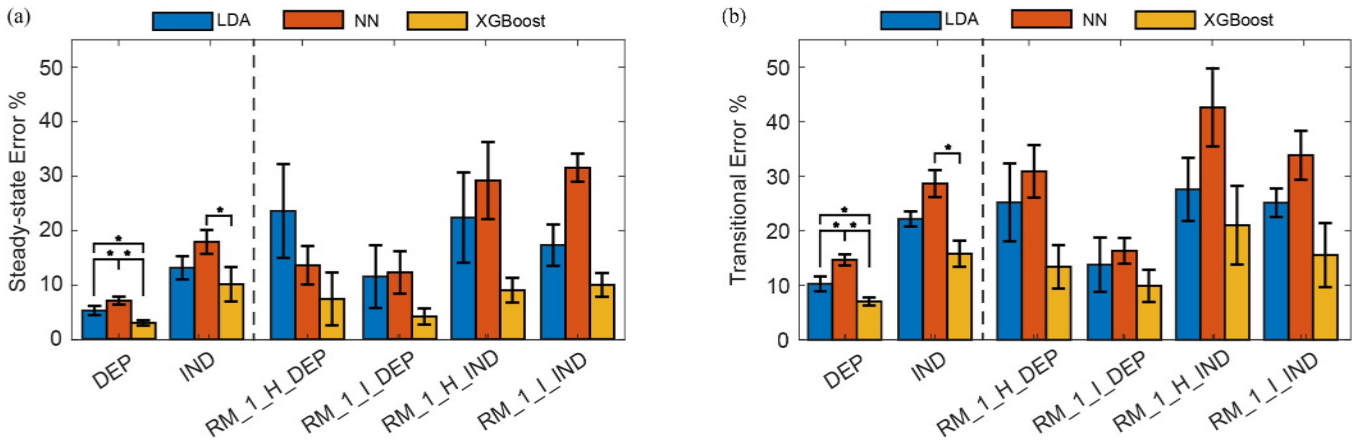


Fig. 3. Three different models (LDA/NN/XGBoost) were compared for the classification of ambulation mode in ramps, stairs and level-ground, resulting in XGBoost outperforming other models. The y-axis shows the performance metric, consisting of the error in classification during steady state walking within a mode and the error of transitioning between modes. The x-axis show the six conditions of evaluation: subject dependent (i.e. training and testing on the same subject), subject independent (i.e. training on all subjects but the testing subject), and remove-1 condition for the stair height and ramp inclination for both (a) dependent and (b) independent. Error bars represent $\pm$ standard error of the mean. Asterisks indicate statistical significance ($p < 0.05$).

groups have implemented ensemble algorithms in gait classification tasks [33]–[36]. To the authors' knowledge, this is a new algorithm that has not been implemented in the field of lower-limb powered prostheses.

One novel aspect of this study compared to prior literature is having an expanded mechanical sensor set embedded on the prosthesis which includes 6-axis IMUs on the foot, shank and thigh, a 6-axis load cell, and joint encoders at the knee and ankle. Furthermore, our experimental paradigm allows for a unique data set to test generalizability across multiple stair heights and ramp inclination angles, and lastly exploring the use of a new algorithm for wearable robotics (XGBoost) on classifier performance. Thus, our first hypothesis is that more complex algorithms like XGBoost will improve the accuracy of the classification and scale across different grades of terrain by learning patterns that are not described by more simple methods, especially when using inputs from multiple sensors. Secondly, we hypothesized that adding extra mechanical sensors can help to improve the performance of the user-independent classifiers compared to its dependent counterparts. This study will help provide meaningful information for future development of user-intent recognition systems that can be clinically relevant.

TABLE I
FINAL OPTIMIZED PARAMETERS

	NN	XGBoost
DEP	Layers: 1 Nodes: 50 Optimizer: <i>Adam</i> Learning rate: 0.001 Activation function: <i>relu</i> Batch size: 32	Max depth: 1 Lambda: 0.5 Min split loss: 0 Learning rate: 0.3
IND	Layers: 3 Nodes: 10 Optimizer: <i>Adam</i> Learning rate: 0.001 Activation function: <i>tanh</i> Batch size: 128	Max depth: 3 Lambda: 1 Min split loss: 0.1 Learning rate: 0.3

II. METHODS

A. Powered Knee and Ankle Device

Our study utilized a powered knee and ankle prosthesis that features two independently controlled joints at the knee and ankle, providing powered assistance in the sagittal plane; a

more detailed presentation of the prosthesis can be found in a previous paper [37], [38]. Briefly, the prosthesis includes six embedded mechanical sensors: two joint incremental encoders (US Digital E5) to measure knee and ankle kinematics, a 6-DOF (degree of freedom) load cell (SRIM3714C2) to measure ground reaction forces and moments, and three 6-axis (accelerometer & gyroscope) inertial measurement units (YOST 3-Space LX embedded) (IMUs). All sensors were collected at 100 Hz except for IMUs, which were sampled at 250 Hz. A three-tier control paradigm was implemented in this study. The low-level controller was responsible for minimizing error between the desired and actual torque profiles. The mid-level controller was an impedance controller paired with a finite state machine. Furthermore, the gait cycle was discretized into four states (early stance, late stance, swing flexion, and swing extension) for each ambulation mode [14]. Detailed approaches of how impedance parameters were tuned were based on previous literature [14], [39]. The high-level controller is responsible for predicting transitions between different ambulation modes (i.e. user intent) and estimating features of different terrain. The focus of this paper was to demonstrate a method of developing a user intent recognition system that could be utilized on wearable robotic devices.

B. Experimental Design

Eight individuals (7 males/1 female, age: 49.63 ± 13.68 years, height: 1.77 ± 0.07 m, mass: 87.31 ± 16.47 kg) with unilateral transfemoral amputation (4R/4L) were recruited and provided informed consent in accordance with the Georgia Institute of Technology Institutional Review Board. The prosthetic device was configured to each user by a certified prosthetist for appropriate comfort and alignment. The prosthetist guided the subjects in adjusting their gait to overcome any exaggerated or over-compensatory movements. When the prosthetist was satisfied with the tuning process, we conducted our collection of ambulation circuits. Users were asked to complete 2 types of ambulation circuits (ramp circuit: level walking (LW), ramp ascent (RA), & ramp descent (RD), stair circuit: level walking (LW), stair ascent (SA), & stair descent (SD)) of each preset condition in our in-lab terrain park area using our powered prosthesis. Our custom built terrain park was adjusted and set to 4 different presets for which 4 ramp trials occurred at 7.8° , 9.2° , 11.0° , and 12.4° and 4 stair trials at 10.2 cm, 12.7 cm, 15.2 cm, and 17.8 cm. Hence a total of 32 trials were collected from each subject across all the different modes. Ambulation mode labels were generated using our finite state machine. Steady state steps (SS) were identified if the previous gait event (heel contact or toe-off) remained in the same event. While transitional steps (TS) were identified if the previous gait event on the previous mode was different on the next mode (e.g. LW_LateStance to SA_SwingFlexion – was labeled as SA).

C. Data Processing and Feature Extraction

To ensure an appropriate input of data to train our mode classifiers, a general workflow was implemented to investigate and compare multiple machine learning algorithms for predicting

locomotion mode. We had 6 embedded sensors on the prosthesis (2 encoders, 3 IMUs, and 1 load cell). We had 2 channels from each encoder and 6 channels from each IMU and the loadcell. We extracted 5 feature types (minimum, maximum, mean, standard deviation, and ending value) resulting in a total of 140 features (28 channels $\times$ 5 feature types = 140 total features) for a given window [15], [17], [20]. We ran two sequential forward simulations to see if certain feature types and channels were needed. It was found that removing any given feature type did not result in a decrease in classification error. Similar results were seen in the channel simulation. Hence, to be conservative, all the features were kept, since there was no evidence of overfitting from these simulations. The experimental data was neither based on timing or % gait cycle, but rather the 6-DOF loadcell to transition between phases of each ambulation mode as seen in previous studies [14]. Gait decisions were made at toe off (weight under a threshold) and heel contact (weight exceeding a threshold) to create reliable time points for transitioning the device between ambulation modes. A normalization scheme was applied first at the sensor level by dividing the load cell signal by each subject's respective weight. Furthermore, a z-score normalization was explored across all sensors on the feature level, with the load cell showing the best improvement compared to non-normalized data.

D. Locomotion Mode Classifiers

Initially, five algorithms were chosen for performance comparison in mode classification. These algorithms were linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), Naive Bayes (NB), neural networks (NN), and XGBoost. The Bayesian classifiers were selected as being the current standard in the field of low-error classifiers. We ran a performance comparison across these Bayesian techniques in which LDA showed the lowest error. LDA has also been seen in prior work to be the gold standard to compare against [40]. Hence, the model comparison was reduced to 3 models: LDA, NN, and XGBoost. For each phase, a specific classifier was trained to capture the optimal transition point. Depending on the gait mode transition, the time during the gait cycle in which the classifier must make its decision is inherently gait phase specific. This strategy of transitioning is not unique and many groups have used a similar phase dependent scheme to change between gait modes based on gait events, and we adopt a similar approach here [2], [14], [17], [21].

E. Algorithm Optimization

Hyperparameter optimization of NN and XGBoost was completed to ensure model architectures were appropriate for generalizing our mechanical sensor information for the task of mode classification; LDA did not require any additional tuning. Scripts were written for all models and case studies (dependent, independent, remove-one-height/incline) and an initial window size of 250 ms was selected. We started with a directed search of unique hyperparameters for each algorithm. The subset of parameters resulting in the lowest average error between steady state and transitional error was selected until all of the parameters

were swept. In XGBoost, the set of hyperparameters explored included: the learning rate used to influence the convergence to a solution, the maximum allowable tree depth, the regularization term to control the sensitivity, and minimum gain required to further split on a node in the tree. In the NN, the set of hyperparameters included: layers and nodes to determine adequate size of the network needed, optimizer and learning rate to influence the convergence to a solution, and activation function and batch size to limit model complexity.

After model optimization, a window size sweep was performed from 50 ms to 500 ms in increments of 50 ms, with the evaluation metric of taking the average of the steady state and transitional error together. The optimal window size was found to be 250 ms. Specifically, the transitional error had a minimum at 250 ms, with larger error associated with smaller or larger windows; while steady-state error was reduced the most at 250 ms and held approximately constant with larger window sizes.

F. Model Evaluation

Several steps were taken to prevent overfitting of each model. First, six different case studies were explored: dependent (DEP), independent (IND), remove-one-height dependent (RM-1-H-DEP), remove-one-height independent (RM-1-H-IND), remove-one-incline dependent (RM-1-I-DEP), and remove-one-incline independent (RM-1-I-IND). The DEP case study was similar to previous literature where data was trained on each individual subject and evaluated using a remove-one-trial cross validation. The IND case study was also taken as a traditional method of training on all users except for one which in turn became the test set. Thus, in these first two cases, both the train and test set had examples from the same stair height and ramp incline conditions. The RM-1-H-DEP and RM-1-I-DEP conditions were trained with all of the ramps and stairs conditions except for the unknown height or incline that served as the test set. This procedure was repeated until each height or incline was included in the test set. Lastly, the RM-1-H-IND and RM-1-I-IND conditions were trained with all the data except for all of the subjects' data at a specific height or incline and the removed subject's data. These were then tested on the removed subject's specific height or incline that was not in the train set. Similar to the RM-1-DEP cases, this procedure was repeated until each height or incline was swept. Our error criteria for evaluating the model's performance can be seen in the following equations, where SS is steady state steps, TS is transitional steps, HC is heel contact, and TO is toe off. This error was then averaged across subjects for both the steady state and transitional errors.

$$SS_error = 1 - \frac{SS_correct_HC + SS_correct_TO}{SS_total_HC + SS_total_TO} \quad (1)$$

$$TS_error = 1 - \frac{TS_correct_HC + TS_correct_TO}{TS_total_HC + TS_total_TO} \quad (2)$$

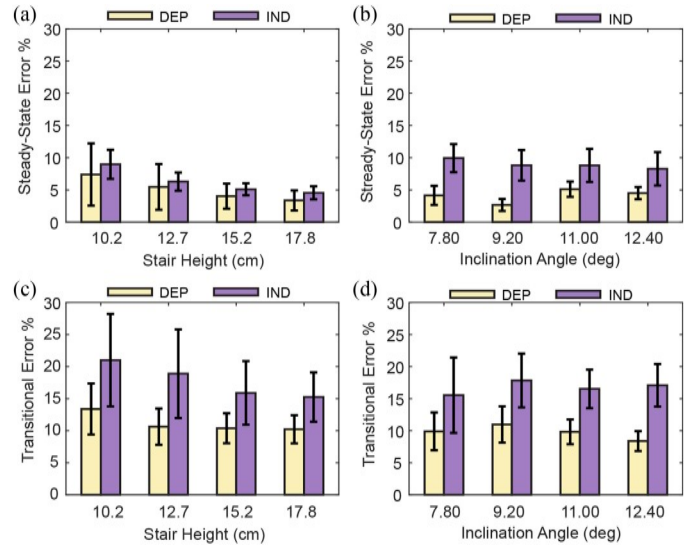


Fig. 4. XGBoost showed the best performance across all case studies. It can be seen that this model can generalize to different stair heights and inclination angles with relatively low error. The y-axes show the error for each condition - (a) RM-1-H-DEP, (b) RM-1-I-DEP, (c) RM-1-H-IND, and (d) RM-1-I-IND, while the x-axes show the 4 preset conditions for the 2 types of ambulation circuits. Results are presented for both DEP and IND cases to show how well the algorithm behaves under different validation strategies. Error bars represent the ± 1 standard error of the mean.

$$sensor_error = 1 - \frac{SS_error + TS_error}{2} \quad (3)$$

G. Statistical Analysis

We conducted a one-way repeated measures analysis of variance (ANOVA) to compare the model performance across only the DEP and IND conditions ($\alpha = 0.05$). The independent variable was the machine learning model (LDA/NN/XGBoost). A Dunn-Bonferroni post-hoc correction was used to compute the statistical differences between each condition (Minitab 19.0, USA).

III. RESULTS

A. Model Comparison

In the DEP case for steady state error, XGBoost ($2.93\% \pm 0.49\%$) was found to be the best model compared to LDA ($5.20\% \pm 0.85\%$) and NN ($7.01\% \pm 0.73\%$) ($p < 0.05$). Similar results were found in the transitional error case, where XGBoost ($7.03\% \pm 0.74\%$) had the lowest error compared to LDA ($10.26\% \pm 1.36\%$) and NN ($14.66\% \pm 1.02\%$) ($p < 0.05$). In the IND case for steady state error, XGBoost ($10.12\% \pm 3.16\%$) was found only to be statistically different than NN ($17.89\% \pm 2.19\%$). Similar trend was seen in the transitional error, where XGBoost ($15.78\% \pm 2.39\%$) was found to be only statistically different than NN ($28.65\% \pm 2.48\%$).

B. Remove-One-Preset Comparison

From the model comparison above, XGBoost was selected as our best model, and the results for Fig. 4 are only displayed for

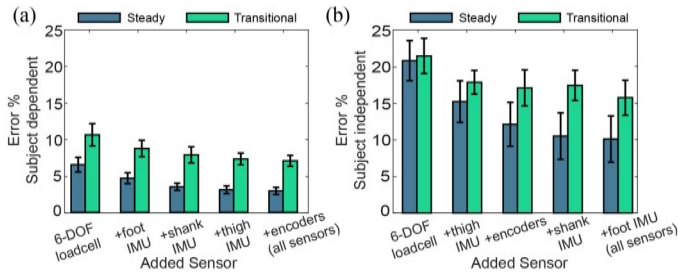


Fig. 5. The XGBoost algorithm was evaluated incrementally for each sensor that was selected on a sequential forward feature selection process. This was implemented for both (a) subject dependent and (b) subject independent models. In both cases, the loadcell was the most favorable sensor for locomotion mode classification. For example, in a) the first bars show the model trained with only the features of the loadcell (6 channels $\times$ 5 feature types = 30 features), the second bars show adding the foot IMU (30 previous features from loadcell + 30 new features), and so on until all the features were trained upon - 140 total features). The y-axes show the error for each condition, while the x-axes show the added sensor to the pool on each iteration. Error bars represent the $\pm$ standard error of the mean.

this model. Across all of the remove-one-incline conditions, the transitional and steady state error rates were consistent across incline rates. However, for remove-one-stair height conditions, the transitional and steady-state error rate decreased with large stair heights. The average steady error for user-dependent classifiers across both preset conditions was $4.59\% \pm 2.05\%$, while the transitional error was $7.60\% \pm 2.57\%$. The average steady error for user-independent classifiers across both preset conditions was $6.54\% \pm 1.92\%$, while the transitional error was $17.26\% \pm 4.92\%$.

C. Sensor Contribution

A sequential forward sensor selection using the XGBoost algorithm revealed that in both DEP and IND cases, the inclusion of all sensors yielded the lowest error ($p < 0.05$). In this analysis, each sensor's features were independently tested. In the first iteration, we took one of the sensors and its features (6 total sensors, 140 total features: 6-DOF loadcell – 30 features, foot IMU – 30 features, shank IMU – 30 features, thigh IMU – 30 features, and joint encoders – 20 features) and determined which sensor, when removed from the training set of the model, would yield the highest test error implying that this was the most useful sensor needed for the mode classifier. If selected, the sensor was kept in the feature space, while the remaining sensors were tested again in another iteration; this continued until all sensors were swept. The error metric used was the average of the steady state (SS) and transitional (TS) errors to determine what combination of sensors would yield the lowest error (Eq. 3). Across both steady state and transitional errors, the forward sensor selection algorithm chose the load cell as the best sensor that contributed the lowest error across both test (DEP and IND) cases. (Fig. 5).

D. XGBoost Confusion Matrices

We created several confusion matrices to show how the model performed across individual modes. Note LW data was present in both classifier types. We concatenated across subjects and

combined steady state and transitional errors to show how XGBoost performed in classifying each mode. In the DEP case, XGBoost correctly classified 3170/3227 (98.23%) level walking (LW) steps, 592/633 (93.52%) ramp ascent (RA) steps, 594/643 (93.84%) ramp descent (RD) steps, 400/421 (95.01%) stair ascent (SA) steps, and 268/299 (89.63%) stair descent (SD) steps. Overall, across all modes in the DEP case, XGBoost correctly classified 5024/5223 steps (96.19%). In the IND case, XGBoost correctly classified 3098/3227 (96.00%) level walking (LW) steps, 516/633 (81.52%) ramp ascent (RA) steps, 457/643 (71.07%) ramp descent (RD) steps, 391/421 (92.87%) stair ascent (SA) steps, and 233/299 (77.93%) stair descent (SD) steps. Overall, across all modes in the IND case, XGBoost correctly classified 4695/5223 steps (89.89%).

IV. DISCUSSION

Our study explored two key features in enhancing the locomotion mode classification performance by 1) comparing different model complexities of current state-of-the-art models to XGBoost and evaluating the performance of these algorithms across users and different stair heights and inclination angles, and 2) understanding whether the user-independent classifiers with the addition of extra sensors could achieve similar performance to the dependent classifiers.

As we explored the effect of model complexity across different case studies, XGBoost outperformed both LDA and NN in the steady state error across independent and dependent models ($p < 0.05$), while only outperforming NN in the transitional case ($p < 0.05$). Therefore, our first hypothesis was partially accepted in that the most complex algorithm (XGBoost) performed the best, but simply adding complexity did not yield benefits as LDA still outperformed more complex NN in certain situations, and is rejected that more complex algorithms are better for improving performance. Thus, an optimal level in complexity can reduce classification error. Across all case studies performed, XGBoost showed best performance which is one step closer to creating algorithms that can generalize across multiple grades of terrain. Note that RM-1-cases were generally more difficult for a machine learning algorithm to predict modes compared to a DEP or IND setup. This is because the classifier must generalize to a ramp incline or stair height that does not exist in the training data. Our goal was to understand if these algorithms could learn on limited data and generalize to unknown environmental conditions.

Although sensor (Fig. 5), channel (not shown) and feature type (not shown) selection were analyzed, no sensors/channels or feature types all were useful for reducing user-independent classification errors. Our second hypothesis on the addition of sensor information was accepted. It was shown that the inclusion of sensors continually improved model performance across both DEP and IND cases. Results indicated that the 6-DOF loadcell was the most essential sensor. Additional analysis could be performed to determine the influence of specific feature components from each sensor to minimize the amount of information that is extracted from the sensors while maintaining model performance.

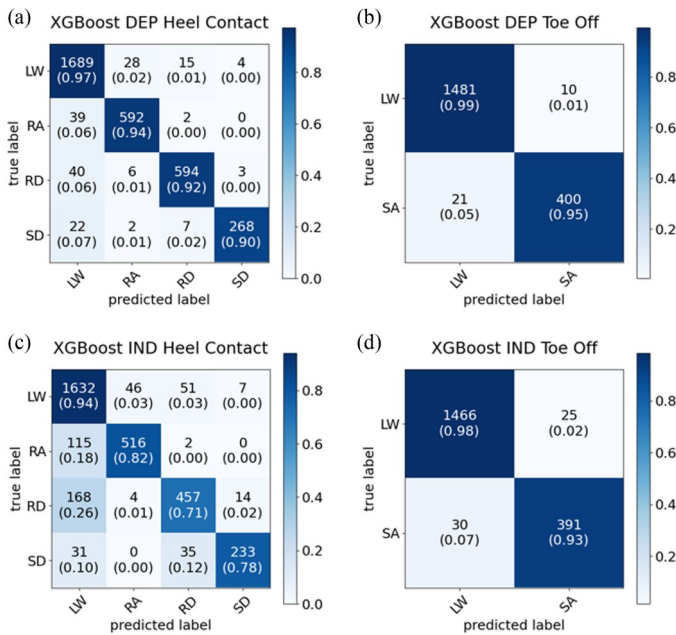


Fig. 6. Confusion matrices for our best model (XGBoost) to show individual classification accuracies for each mode and phase type - (a) DEP HC classifier, (b) DEP TO classifier, (c) IND HC classifier, and (d) IND TO classifier). The results show that in the DEP case, XGBoost had a 96.19% classification accuracy and that in the IND case, XGBoost had a 89.89% classification accuracy. The y-axes show the true label while the x-axes show the predicted label.

We believe that direct comparisons cannot be made to prior literature due to our dataset's unique inclusion of multiple stair heights and inclination angles which do not exist in previous studies. Hence, we found other literature methods that created intent recognition systems; LDA and NN was commonly used as a baseline and we applied that same method to make an equal comparison to our dataset. The results indicate that XGBoost shows potential in generalizing across subjects when employing a user independent intent recognition system. We observed that XGBoost had some difficulty in differentiating between LW and RA (Fig. 6). Future work should look into combining these modes as one label as seen in prior work to see if there is an improvement in model performance [21], [24]. Similar results were seen in Young *et al.*, where steady state and transitional errors of 8% and 13% were achieved but required more complicated dynamic bayesian networks (DBN - useful methods that incorporate time history information using current observations and prior probabilities) and mode specific architectures which are much more challenging to implement than the methods presented here [16], [24].

One limitation of our study is the small number of subjects ($N = 8$) especially when trying to create a user independent system. The purpose of each ambulation circuit was to capture the behavior of traversing different terrain types from level walking to allow for inclusion of both steady state and mode transitional steps. However, the amount of training data is relatively small. For every ambulation circuit, there are only 4 transitional steps compared to 12–16 steady state steps. Future work is still required to address the issue of achieving smaller

transitional errors with a small training dataset. Lastly, our study was limited in that it was just an offline analysis. Previous studies have indicated that implementing these models in real-time must be done properly in order to avoid the dangerous outcomes of misclassification errors [10], [15], [22]. To make these algorithms prevalent in prosthetic controllers for clinical applications, real-time validation of these models is imperative.

V. CONCLUSION

Our study investigated machine learning models for improving user independent and dependent locomotion mode classification. We found that XGBoost had the lowest errors compared to our other models (DEP SS Error: $2.93\% \pm 0.49\%$, DEP TS Error: $7.03\% \pm 0.74\%$, IND SS Error: $10.12\% \pm 3.16\%$, and IND TS Error: $15.78\% \pm 2.39\%$). Our approach showed that finding an optimal model complexity could improve model performance and generalize across different stair heights and inclination angles. Future work will continue to explore enhancing these classification models for them to be used in real-time applications and progress the long-term goal of promoting this technology into clinical settings.

ACKNOWLEDGMENT

We would like to thank our undergraduate team who helped with data collection and analysis which included Alice Bok and Daniel de Matheu. We would also like to thank all of our participants who took part in this study.

REFERENCES

- [1] F. Sup, A. Bohara, and M. Goldfarb, "Design and control of a powered transfemoral prosthesis," *Int. J. Robot. Res.*, vol. 27, no. 2, pp. 263–273, Feb. 2008.
- [2] B. E. Lawson, J. Mitchell, D. Truex, A. Shultz, E. Ledoux, and M. Goldfarb, "A robotic leg prosthesis: Design, control, and implementation," *IEEE Robot. Autom. Mag.*, vol. 21, no. 4, pp. 70–81, Dec. 2014.
- [3] E. J. Rouse, L. M. Mooney, E. C. Martinez-Villalpando, and H. M. Herr, "Clutchable series-elastic actuator: Design of a robotic knee prosthesis for minimum energy consumption," in *Proc. IEEE Int. Conf. Rehabil. Robot.*, to be published, doi: [10.1109/ICORR.2013.6650383](https://doi.org/10.1109/ICORR.2013.6650383).
- [4] K. Ziegler-Graham, E. J. MacKenzie, P. L. Ephraim, T. G. Trivison, and R. Brookmeyer, "Estimating the prevalence of limb loss in the United States: 2005 to 2050," *Arch. Phys. Medicine Rehabil.*, vol. 89, no. 3, pp. 422–429, Mar. 2008.
- [5] L. Nolan and A. Lees, "The functional demands on the intact limb during walking for active trans-femoral and trans-tibial amputees," *Prosthetics Orthotics Int.*, vol. 24, no. 2, pp. 117–125, Aug. 2000.
- [6] R. Gailey, K. Allen, J. Castles, J. Kucharik, and M. Roeder, "Review of secondary physical conditions associated with lower-limb amputation and long-term prosthesis use," *J. Rehabil. Res. Develop.*, vol. 45, no. 1, pp. 15–29, 2008.
- [7] K. A. Ingraham, N. P. Fey, A. M. Simon, and L. J. Hargrove, "Assessing the relative contributions of active ankle and knee assistance to the walking mechanics of transfemoral amputees using a powered prosthesis," *PloS One*, vol. 11, no. 1, Jan. 2016, Art. no. 0147661.
- [8] 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," *Clinic. Biomech.*, vol. 55, pp. 65–72, Jun. 2018.
- [9] A. M. Simon, N. P. Fey, K. A. Ingraham, S. B. Finucane, E. G. Halsne, and L. J. Hargrove, "Improved weight-bearing symmetry for transfemoral amputees during standing up and sitting down with a powered knee-ankle prosthesis," *Arch. Phys. Medicine Rehabil.*, vol. 97, no. 7, pp. 1100–1106, Jul. 2016.

- [10] L. J. Hargrove *et al.*, "Intuitive control of a powered prosthetic leg during ambulation: A randomized clinical trial," *J. Amer. Med. Assoc.*, vol. 313, no. 22, pp. 2244–2252, 2015.
- [11] M. R. Tucker *et al.*, "Control strategies for active lower extremity prosthetics and orthotics: A review," *J. NeuroEng. Rehabil.*, vol. 12, pp. 1–30, Jan. 2015, doi: [10.1186/1743-0003-12-1](https://doi.org/10.1186/1743-0003-12-1).
- [12] H. M. Herr and A. M. Grabowski, "Bionic ankle-foot prosthesis normalizes walking gait for persons with leg amputation," *Proc. Roy. Soc. B: Biol. Sci.*, vol. 279, no. 1728, pp. 457–464, Feb. 2012.
- [13] E. R. Esposito, J. M. A. Whitehead, and J. M. Wilken, "Step-to-step transition work during level and inclined walking using passive and powered ankle-foot prostheses," *Prosthetics Orthotics Int.*, vol. 40, no. 3, pp. 311–319, Jun. 2016.
- [14] A. M. Simon *et al.*, "Configuring a powered knee and ankle prosthesis for transfemoral amputees within five specific ambulation modes," *PloS One*, vol. 9, no. 6, 2014, Art. no. e99387.
- [15] H. A. Varol, F. Sup, and M. Goldfarb, "Multiclass real-time intent recognition of a powered lower limb prosthesis," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 3, pp. 542–551, Mar. 2010.
- [16] A. J. Young, A. M. Simon, N. P. Fey, and L. J. Hargrove, "Intent recognition in powered lower limb prosthesis using time history information," *Ann. Biomed. Eng.*, vol. 42, no. 3, pp. 631–641, Mar. 2013.
- [17] A. J. Young, A. M. Simon, and L. J. Hargrove, "A training method for locomotion mode prediction using powered lower limb prostheses," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 3, pp. 671–677, May 2014.
- [18] B. Y. Su, J. Wang, S. Q. Liu, M. Sheng, J. Jiang, and K. Xiang, "A CNN-based method for intent recognition using inertial measurement units and intelligent lower limb prosthesis," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 5, pp. 1032–1042, May 2019.
- [19] R. B. Woodward, J. A. Spanias, and L. J. Hargrove, "User intent prediction with a scaled conjugate gradient trained artificial neural network for lower limb amputees using a powered prosthesis," in *Proc. Annu. Int. Conf. IEEE Eng. Medicine Biol. Soc.*, Oct. 2016, pp. 6405–6408.
- [20] H. Huang, F. Zhang, L. J. Hargrove, Z. Dou, D. R. Rogers, and K. B. Englehart, "Continuous locomotion-mode identification for prosthetic legs based on neuromuscular—Mechanical fusion," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 10, pp. 2867–2875, Oct. 2011.
- [21] A. M. Simon *et al.*, "Delaying ambulation mode transition decisions improves accuracy of a flexible control system for powered knee-ankle prosthesis," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 8, pp. 1164–1171, Aug. 2017.
- [22] J. A. Spanias, A. M. Simon, S. B. Finucane, E. J. Perreault, and L. J. Hargrove, "Online adaptive neural control of a robotic lower limb prosthesis," *J. Neural Eng.*, vol. 15, no. 1, Feb. 2018, Art. no. 016015.
- [23] L. J. Hargrove, K. Englehart, and B. Hudgins, "A comparison of surface and intramuscular myoelectric signal classification," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 5, pp. 847–853, May 2007.
- [24] A. J. Young and L. J. Hargrove, "A classification method for user-independent intent recognition for transfemoral amputees using powered lower limb prostheses," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 2, pp. 217–225, Feb. 2016.
- [25] D. Nielsen, "Tree boosting with XGBoost why does XGBoost win "Every" machine learning competition?" M.S. thesis, Dept. Math. Sci., Faculty Inf. Technol., Math. Elect. Eng., Norwegian Univ. Sci. Technol., Gjøvik, Norway, 2016. [Online]. Available: <http://hdl.handle.net/11250/2433761>
- [26] B. Semiz, S. Hersek, D. C. Whittingslow, L. A. Ponder, S. Prahalad, and O. T. Inan, "Using knee acoustical emissions for sensing joint health in patients with juvenile idiopathic arthritis: A pilot study," *IEEE Sensors J.*, vol. 18, no. 22, pp. 9128–9136, Nov. 2018.
- [27] H. Lu, M. Pinaroc, M. Lv, S. Sun, H. Han, and R. C. Shah, "Locomotion recognition using XGboost and neural network ensemble," in *Proc. Adjunct ACM Int. Joint Conf. Pervasive Ubiquitous Comput. and Proc. ACM Int. Symp. Wearable Comput.*, Sep. 2019, pp. 757–760.
- [28] Y. Ye, C. Liu, N. Zemititi, and C. Yang, "Optimal feature selection for EMG-based finger force estimation using lightGBM model," in *Proc. 28th IEEE Int. Conf. Robot Human Interactive Commun.*, to be published, doi: [10.1109/RO-MAN46459.2019.8956453](https://doi.org/10.1109/RO-MAN46459.2019.8956453).
- [29] A. Kadrolkar and F. C. Sup, "Intent recognition of torso motion using wavelet transform feature extraction and linear discriminant analysis ensemble classification," *Biomed. Signal Process. Control*, vol. 38, pp. 250–264, Sep. 2017.
- [30] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Aug. 2016, pp. 785–794.
- [31] S. Ben Taieb and R. J. Hyndman, "A gradient boosting approach to the Kaggle load forecasting competition," *Int. J. Forecasting*, vol. 30, no. 2, pp. 382–394, Apr. 2014.
- [32] R. Mitchell and E. Frank, "Accelerating the XGBoost algorithm using GPU computing," *PeerJ. Comput. Sci.*, vol. 2017, no. 7, p. e127, Jul. 2017, doi: [10.7717/peerj-cs.127](https://doi.org/10.7717/peerj-cs.127).
- [33] N. Shawen *et al.*, "Fall detection in individuals with lower limb amputations using mobile phones: Machine learning enhances robustness for real-world applications," *JMIR mHealth uHealth*, vol. 5, no. 10, p. e151, Oct. 2017, doi: [10.2196/mhealth.9177](https://doi.org/10.2196/mhealth.9177).
- [34] C. Wang, X. Wu, Y. Ma, G. Wu, and Y. Luo, "A flexible lower extremity exoskeleton robot with deep locomotion mode identification," *Hindawi*, vol. 2018, 2018, Art. no. 5712108.
- [35] F. Peng, W. Peng, and C. Zhang, "Evaluation of sEMG-based feature extraction and effective classification method for gait phase detection," in *Commun. Comput. Inform. Sci.*, vol. 1006, Berlin, Germany: Springer-Verlag, Nov. 2019, pp. 138–149.
- [36] S. Nakagome, T. P. Luu, Y. He, A. S. Ravindran, and J. L. Contreras-Vidal, "An empirical comparison of neural networks and machine learning algorithms for EEG gait decoding," *Scientific Rep.*, vol. 10, no. 1, pp. 1–17, Dec. 2020.
- [37] H. Zhao, E. Ambrose, and A. D. Ames, "Preliminary results on energy efficient 3D prosthetic walking with a powered compliant transfemoral prosthesis," in *Proc. IEEE Int. Conf. Robot. Autom.*, 2017, pp. 1140–1147.
- [38] K. Bhakta, J. Camargo, and A. J. Young, "Control and experimental validation of a powered knee and ankle prosthetic device," in *Proc. Dyn. Syst. Control Conf.*, to be published, doi: [10.1115/DSCC2018-9218](https://doi.org/10.1115/DSCC2018-9218).
- [39] K. Bhakta, J. Camargo, P. Kunapuli, L. Childers, and A. Young, "Impedance control strategies for enhancing sloped and level walking capabilities for individuals with transfemoral amputation using a powered multi-joint prosthesis," *Mil. Med.*, vol. 185, no. Supplement_1, pp. 490–499, Jan. 2020.
- [40] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 7, pp. 848–854, Jul. 2003.

Appendix C: American Society of Biomechanics Conference Abstract

Title: Restoring Functional Gait of Individuals with Transfemoral Amputation using a Powered Prosthesis

Authors: Krishan Bhakta, Jonathan Camargo, William Compton, Kinsey Herrin, and Aaron Young

Date of Publication: August 5, 2020

Restoring Functional Gait of Individuals with Transfemoral Amputation using a Powered Prosthesis

Krishan Bhakta¹, Jonathan Camargo^{1,2}, William Compton¹, Kinsey Herrin^{1,2}, Aaron Young^{1,2}

¹Woodruff School of Mechanical Engineering, Georgia Institute of Technology, Atlanta GA, 30332 USA

²Institute for Robotics and Intelligent Machines, Georgia Institute of Technology, Atlanta GA, 30332 USA

Email: kbhakta3@gatech.edu

Introduction

When walking, individuals with transfemoral amputation (TFA) use compensatory strategies which often lead to asymmetric joint biomechanics, chronic leg and back pain, joint degradation, increased energetic demands, and increased chance of osteoarthritis.^{1,2} Specifically, the hip has to compensate for power lost from missing joints.³ Powered prostheses are one option of improving gait as they are able to provide similar biological assistance profiles across different walking modes.⁴ Our hypothesis is that a powered prosthesis will generate improved bilateral biomechanics than current clinically available passive prostheses, which was initially evaluated based on joint kinematic comparisons.

Methods

Three subjects with a unilateral transfemoral amputation (male, 51 ± 21.1 years old, 1.78 ± 0.07 m, 82 ± 15.5 kg, K3/K4) consented to participate in this IRB approved study. Subjects performed level and sloped walking on an instrumented treadmill (Bertec, Columbus, OH) using their everyday prosthesis and our powered knee and ankle prosthesis at 0 deg, +7.5 deg, and -7.5 deg. Data was collected using a motion capture system (Vicon, Centennial, CO). Analysis was performed using custom built prosthetic models in OpenSim, an open-source musculoskeletal modeling and simulation platform.

Results and Discussion

The results show that the inverse kinematics (IK) were symmetrical to biological signals when using the powered device versus their passive device. Specifically, the ankle kinematics on the prosthetic side show increased plantarflexion for both the level and incline walking trials. Furthermore, the intact side shows a reduction in the amount of plantarflexion explained by the ability of the prosthesis to contribute power to push the user forward. No

significant changes were seen in the knee kinematics. It also can be seen that there no major changes in the hip kinematics which may be explained by the additional mass of our prosthetic device as the user may still have to compensate with their hip joint to a certain extent. With the powered prosthesis, the assistance shown during these walking tasks could potentially help reduce the risk of future hip and back related musculoskeletal pathologies. The key result is that powered prosthetic technology may be helpful in restoring functional gait across multiple ambulation modes.

Significance

Creating smarter powered prostheses for assisting TFA is an important area of research as these devices can restore lost biomechanical function and potentially improve quality of life. For this type of technology to be translated to modern clinical practice, these devices must show improved efficacy over current clinical standards. This is one step in allowing powered prostheses to restore seamless and natural movement to the user.

Acknowledgments

This work was funded by DOD Award No. W81XWH-17-1-0031.

References

- Highsmith, M. J. *et al. Spine J.* (2018). doi:10.1016/J.SPINEE.2018.08.011
- Morgenroth, D. C., Roland, M., Pruziner, A. L. & Czerniecki, J. M. *Clin. Biomech.* **55**, 65–72 (2018).
- Grumillier, C., Martinet, N., Paysant, J., André, J. M. & Beyaert, C. *J. Biomech.* **41**, 2926–2931 (2008).
- Ingraham, K. A., Fey, N. P., Simon, A. M. & Hargrove, L. J. *PLoS One* **11**, 0147661 (2016).

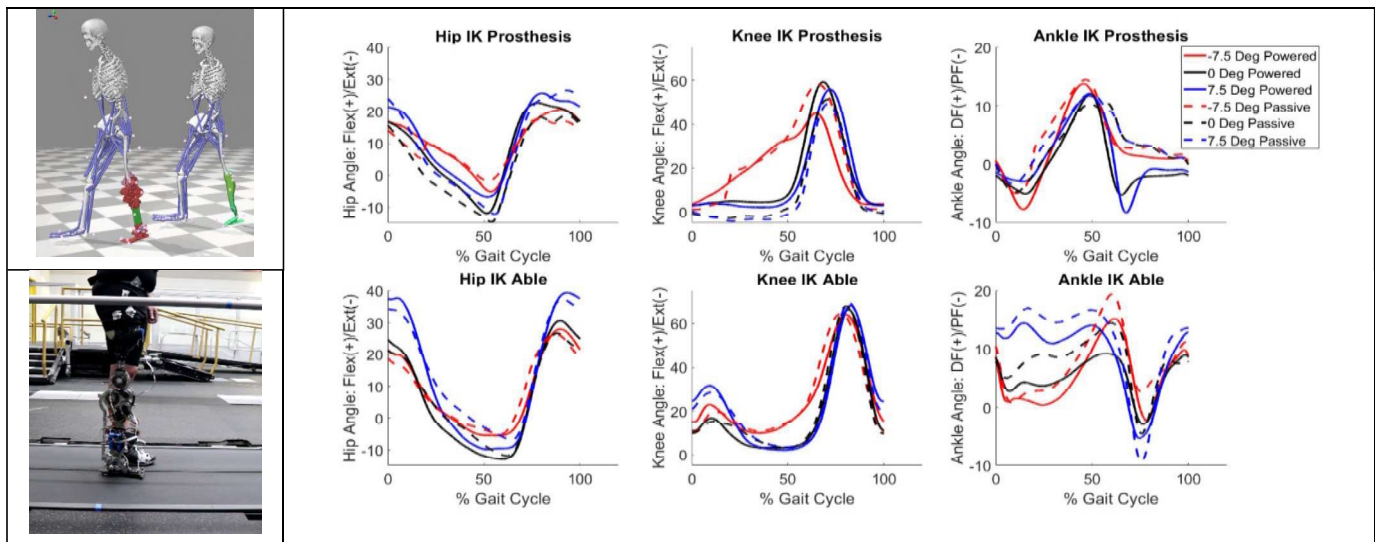


Figure 1: Opensim models of a powered prosthesis and passive prosthesis (top left); one individual wearing our powered prosthesis with motion capture markers placed on both prosthetic and intact side (bottom left); and inverse kinematics for both prosthetic and intact side for three modes of treadmill walking: level ground (0 deg), incline (+7.5 deg), and decline (-7.5 deg).

Appendix D: American Society of Biomechanics Conference Abstract

Title: User- and Speed-Independent Slope Estimation for Lower Extremity Wearable Devices

Authors: Jairo Maldonado, Krishan Bhakta, Jonathan Camargo, and Aaron Young

Date of Publication: August 5, 2020

Jairo Y. Maldonado-Contreras^{1*}, Krishan Bhakta¹, Jonathan Camargo¹, and Aaron J. Young¹

¹School of Mechanical Engineering, Georgia Institute of Technology, Atlanta, GA 30332 USA

Email: jairoymc@gatech.edu

Introduction

As more powered prostheses and exoskeletons enter real-world settings, it is important to adapt assistance profiles in dynamic environments using slope level information. Adaptive assistance profiles based on environmental information can help wearable devices keep up with real-time changes in human biomechanics and maximize assistance benefits. Advancements in intention recognition (IR) algorithms have enabled wearable devices to autonomously assist users across different terrains (e.g., ramps and stairs) [1]. IR algorithms are capable of classifying ramps of different slope levels without the need for slope level estimations, but assistance profiles typically remain constant or are scaled based on encoded joint trajectories. The inclusion of slope estimation algorithms and torque scaling equations in the control of wearable devices offer a more natural and effective interface between users and their environment.

Numerical solutions for slope estimation using inertial measurement units (IMUs) have been shown to be inaccurate due to sensor drift and variations in walking speed [2][3]. Recent work suggests that machine learning (ML) models trained with electromyography (EMG) and mechanical sensor data can accurately estimate slopes at different speeds (1.3° RMSE) [4]. A limitation of this work is that each slope level was estimated for a short range of speeds.

We hypothesize that training a slope estimator with only mechanical sensor data collected on slope levels across a large range walking speeds can accurately estimate slopes independent of the user and walking speed. Our methodology is expected to generate robust slope estimators that could be readily integrated into the control systems of various wearable devices.

Methods

This study focuses on evaluating the performance of ML models in estimating a user's slope level while walking on a speed-varying treadmill. Nine able-bodied subjects were fitted with three 6-axis IMUs (foot, shank and thigh) and three goniometers (ankle, knee, and hip). Thirteen static and five dynamic walking trials were collected for each subject. During static trials, slope levels (-15° to $+15^\circ$, incremented by 2.5°) were held constant while walking speeds changed from 0.6 to 1.4 m/s. During dynamic trials, walking speeds of 1.0 and 1.2 m/s were held constant while slope levels changed from 0° to 10° .

Slope estimation algorithms were evaluated for sensor suites commonly found on ankle prostheses, knee-ankle prostheses, and hip exoskeletons. Signals were filtered and segmented into sliding windows of data, incremented by 50 ms. Mean, standard deviation, min, max, and ending value features were extracted from each window. Analyses across different normalization methods, sliding window sizes, gait phases, and ML models were conducted to minimize slope estimation errors. The performance of neural network (NN), XGBoost (XGB), and linear regression (LNR) models were assessed. The phase dependency of the models was explored across four gait cycle types: 1-phase, 2-phase, 3-phase, and 4-phase. Tested window sizes ranged between 200 ms to 500 ms, incremented by 50 ms.

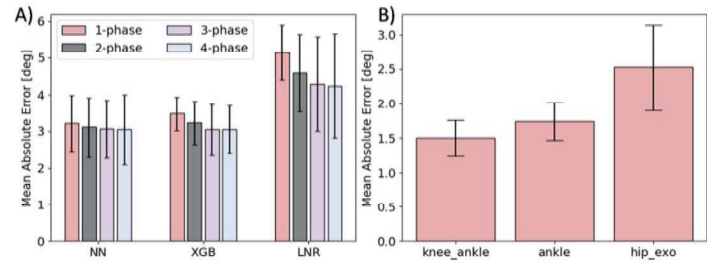


Figure 1: A) Static trial non-optimized model performance across gait cycle types for the knee-ankle case (250 ms window size). B) Optimized XGBoost model performance across all sensor suites using the 1-phase gait cycle analysis method and a 500 ms window size.

Results and Discussion

For static trials, the NN and XGB model similarly outperformed the LNR model across each phase, for each sensor suite, including the knee-ankle case (Fig. 1A). The XGB model was selected over the NN model for hyperparameter optimization due to its lower average MAE variance. Since there was no significant difference between gait cycle types, the 1-phase gait cycle was selected due to its simplicity. With the optimal window size of 500 ms, static trial average MAE errors of $1.500 \pm 0.258^\circ$, $1.739 \pm 0.276^\circ$, $2.522 \pm 0.618^\circ$ were achieved for the knee-ankle, ankle, and hip-exoskeleton sensor suites, respectively (Fig. 1B). Future analyses will test the performance of the proposed ML architectures on the dynamic trials, identify a reduced feature space for each sensor suite, and include a Kalman filter to further reduce errors.

Significance

This user-independent study provides slope estimation solutions that are generalizable to novel users and a variety of wearable devices, including those not explored in this study (e.g., knee exoskeletons). The low errors achieved across dynamic walking speeds and the exclusion of EMG sensors are important steps towards the real-world implementation of slope estimators. Joint torque scaling based on slope level will have a significant impact on the quality of assistance that users receive from lower-extremity wearable devices, which can improve metabolic efficiency, user mobility, and the effectiveness of rehabilitation.

Acknowledgments

The authors would like to acknowledge the NSF Research Traineeship: ARMS Award #1545287. *Supported by an MIT Lincoln Laboratory/GEM Fellowship and Goizueta Fellowship.

References

- [1] A. J. Young et al. *J. Neural Eng.*, vol. 11, no. 5, 2014.
- [2] Q. Li et al., *IEEE International Conference on Rehabilitation Robotics*, 2009, pp. 839–844.
- [3] J. Kim et al., *IEEE International Conference on Rehabilitation Robotics*, 2015, pp. 392–397.
- [4] I. Kang et al., *IEEE International Conference on Rehabilitation Robotics*, 2019, pp. 548–553.

Appendix E: American Academy of Orthotists Prosthetists Abstract

Title: A pilot study comparison of patient reported outcomes following use of a powered knee ankle prosthesis and clinically prescribed passive prosthesis on variable terrains

Authors: Kinsey Herrin, Krishan Bhakta, Jonathan Camargo, and Aaron Young

Date of Publication: December 10, 2020



A pilot study comparison of patient reported outcomes following use of a powered knee ankle prosthesis and clinically prescribed passive prosthesis on variable terrains

Kinsey Herrin^{1,2}, Krishan Bhakta¹, Jonathan Camargo^{1,2}, Aaron Young^{1,2}

¹Woodruff School of Mechanical Engineering, ²Institute of Robotics and Intelligent Machines, Georgia Institute of Technology

INTRODUCTION

Individuals with transfemoral amputation (TFA) experience significant impacts on their physical, social and mental well-being following amputation¹. These patients experience difficulty during ambulatory tasks that require active power², such as ramps or stairs, which are frequently encountered in community environments.³ Unique individual preferences are critical for the successful implementation of assistive technology⁴. Therefore, patient reported outcomes (PRO) associated with advanced devices can provide improved understanding of what users need for successful biopsychosocial rehabilitation. In this study, we report on patient reported outcomes associated with the use of a powered combined knee and ankle prosthesis (PKA) and a passive prosthesis (PP), specifically on non-level terrains.

METHOD

The Georgia Institute of Technology Institutional Review Board approved this study and informed consent was obtained from each subject prior to participation. **Subjects:** Eight subjects with TFA (7 males, 1 female, weight 80.8 kg± 12.63, classified as MFCL K3/K4) secondary to trauma participated. **Procedures:** A combined powered knee and ankle prosthesis (Open source leg, Ann Arbor, MI) was attached to each participant's current socket by a certified prosthetist for appropriate alignment. The device was tuned until the user felt comfortable. Participants then ambulated using both their clinically prescribed PP and the PKA over various terrains, including level ground, stairs, and ramps. Subjects were then asked to complete two PRO, including modified versions of the PEQ-MS (Prosthetic Evaluation Questionnaire-Mobility Scale) and OPUS (Orthotic Prosthetic User Survey) for each device. The OPUS was added at a later date to the protocol and subsequently collected on only 4 subjects. Both measures are based on a 5-point Likert scale with higher scores indicative of improved performance. **Data Analysis:** Data were summarized to include means and standard deviations of each question. A Wilcoxon signed rank test was conducted to determine significant differences between conditions (Minitab18).

RESULTS

Improved performance with the PKA during use on stairs was reported in the PEQ-MS ($p<0.05$) and improved performance with the PKA for walking up a steep hill

approached but did not reach significance ($p=0.059$) (Fig 1). In contrast, improved performance was noted with the PP for 'ability to walk' ($p<0.05$). No other statistical differences were seen, but trends were noted with subjects reporting improved performance walking down stairs and down steep hills with the PKA. Additionally, subjects reported greater perceived benefits in fit, comfort, looks and pain with the PKA over the PP and greater durability of their PP over the PKA in the OPUS (Fig 1) but these differences were not statistically significant.

DISCUSSION

The prevalence of stairs and ramps in community environments is nontrivial for community ambulators with TFA, and assessing PRO is critical to understand the patient perceived benefits associated with advanced technology. When using the PKA, users reported greater ease in negotiating stairs and ramps, improved fit, comfort and pain. Benefits associated with the PKA may be due in part to the powered assist that users receive during locomotion, allowing for a more biomechanically natural gait pattern under challenging tasks such as stair and ramp ascent. Subjects reported some greater perceived benefits with their PP over the PKA, including greater durability and ease in negotiating flat terrains and confined spaces, suggesting areas for improvement of advanced technology, namely in increasing durability, reducing device weight, and simplifying control.

CONCLUSION

While still preliminary, our results suggest patients do perceive improvements in performance and quality of life factors for a powered device during more challenging ambulatory tasks, such as stairs and ramps.

CLINICAL APPLICATIONS

Understanding PRO associated with advanced technology is critical for successful implementation in community ambulators.

REFERENCES

1. Hagberg (2001). POI, 25, 186-194.
 2. Young (2014). IEEE TNSRE, 22(3), 671-677.
 3. Musselman.(2007). Jour Rehab Med, 39(7), 567-574.
 4. Schaffalitzky (2009). POI. 33(2), p. 157-166.
- Funding Acknowledgement:** This work was supported by the Office of the Assistant Secretary of Defense for Health Affairs through the Orthotics and Prosthetics Outcomes Research Program Prosthetics Outcomes Research Award under Award No. W81XWH-17-1-0031.

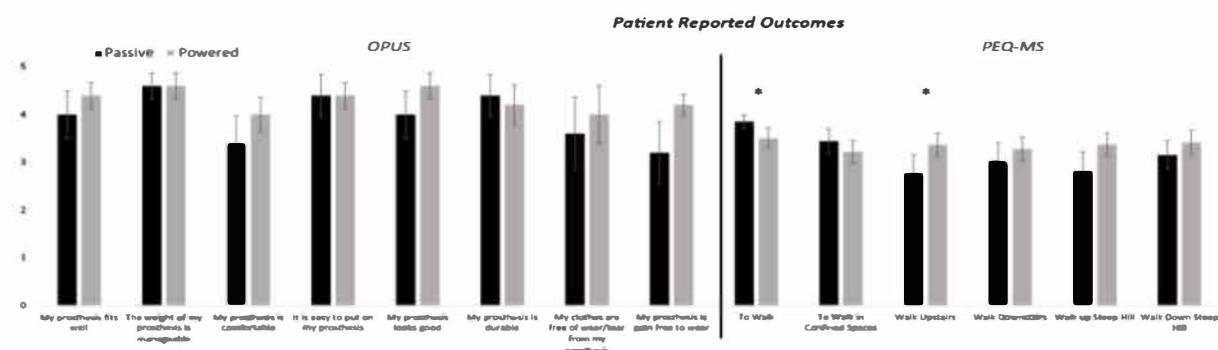


Fig. 1 Patient reported outcomes. * indicates significance at $p<0.05$