Dynamic Adaptation of Robotic Ankle-Foot Prostheses to Compliant Terrain: Reacting to Surface Stiffness Changes in Real-Time

Charikleia Angelidou, Benjamin Chen and Panagiotis Artemiadis*, *IEEE Senior Member*

Abstract— **Real-time adaptability to varying terrain stiffness is a critical factor in enhancing the functionality of robotic ankle-foot prostheses. This paper introduces a novel reactive control framework that classifies surface stiffness and adjusts the prosthesis' behavior in real-time on compliant terrain, utilizing kinematic data from the prosthesis. The framework is tested with three able-bodied participants who completed treadmill walking trials on simulated rigid and compliant surfaces, replicating typical real-life scenarios. The proposed framework employs a Support Vector Machine (SVM) classifier that leverages data such as ankle angle, ankle moment, and Inertial Measurement Unit (IMU) measurements from a powered prosthesis to differentiate between terrains of different stiffness. Results show a classification accuracy of up to 88%, while the classification process is streamlined for rapid decision-making, enabling surface adaptation within milliseconds of initial foot-ground contact. This approach represents a significant step toward creating responsive, user-centric assistive technologies for individuals with lower-limb amputation.**

I. INTRODUCTION

Navigating dynamic terrains, including compliant surfaces and non-level ground, remains a significant challenge for individuals relying on robotic lower-limb prostheses [1,2]. Specifically for individuals with lower-limb amputation (LLA), transitions between surfaces of varying stiffness, such as transitioning from a paved sidewalk to grass or sand, can destabilize gait and compromise user safety [3]. While modern prostheses excel in replicating steady-state walking patterns on rigid terrain [4] and enable safe transitions between different locomotion modes [5, 6], their limited ability to adapt dynamically to surface changes highlights a critical need for improved control frameworks that integrate both environmental sensing and human feedback.

A growing body of research highlights the importance of considering human-robot interaction as a holistic system, where both human and robotic feedback play a critical role in optimizing performance. In this context, effective physical human-robot interaction requires bidirectional communication, encompassing not only the robotic system's ability to adapt to environmental cues but also its capacity to interpret and respond to signals from the human user [7]. Specifically in the context of compliant terrains, recent works have delved deeper into the latter, closely studying the mechanisms of human locomotion over surfaces of varying stiffness and utilizing biomechanical inputs from the human user to predict the upcoming surface stiffness [8, 9].

These works specifically elaborate on a high-level control framework for lower-limb prosthesis, which based on the predicted surface compliance, adjusts the prosthetic limb's behavior before foot contact with the ground, making real-time modifications to match the terrain. The prosthetic limb then moves according to these adjustments and interacts with the environment, a mechanism illustrated in Fig. 1. Feedback from interacting with the compliant environment shows potential for developing reactive control frameworks that refine prosthesis control in real-time, especially during unexpected terrain stiffness changes that could result from sensory occlusion (i.e. not visually perceiving an upcoming compliance change) or distracted walking (i.e. reduced anticipation). Although leveraging the generated prosthesis feedback can enhance both prosthetic functionality and user experience, it remains unexploited in the field of powered prostheses and their adaptation to compliant terrains.

As a preliminary effort to address this gap and improve mobility for individuals with LLA, this paper presents a novel reactive control framework designed to respond to surface stiffness changes in real time, utilizing direct feedback from the user's wearable device or powered prostheses. The goal of this research is to develop a compensatory control mechanism that will identify surface stiffness promptly after the initial contact of the prosthesis with the new surface to improve overall stability and robustness of the prosthesis. By classifying terrain characteristics within a few milliseconds after initial contact with the ground, the goal is to facilitate rapid prosthesis adjustments, mimicking the natural reflexive responses of the human nervous system. The overarching objective of this work is to provide a personalized and intuitive experience for individuals with LLA, ultimately improving the quality of life for users relying on assistive and prosthetic devices.

II. METHODS

The proposed control framework was designed, developed, and tested using experiments with able-bodied participants wearing a robotic ankle-foot prosthesis using a bypass adapter. The methodology encompassed data acquisition, data preprocessing, and segmentation, supervised machine learning model training, as well as real-time simulation testing. The following sections present each of the distinct study components in more detail.

*This material is based upon work supported by the National Science Foundation under Grants No. 2020009, 2015786, 2025797, and 2018905.

Charikleia Angelidou and Panagiotis Artemiadis are with the Mechanical Engineering Department, at the University of Delaware, Newark, DE 19716, USA. cangelid@udel.edu, partem@udel.edu.

Benjamin Chen is with the Department of Mechanical Engineering at the Carnegie Mellon University, Pittsburgh, PA 15213, USA. bc2@andrew.cmu.edu.

*Corrresponding author

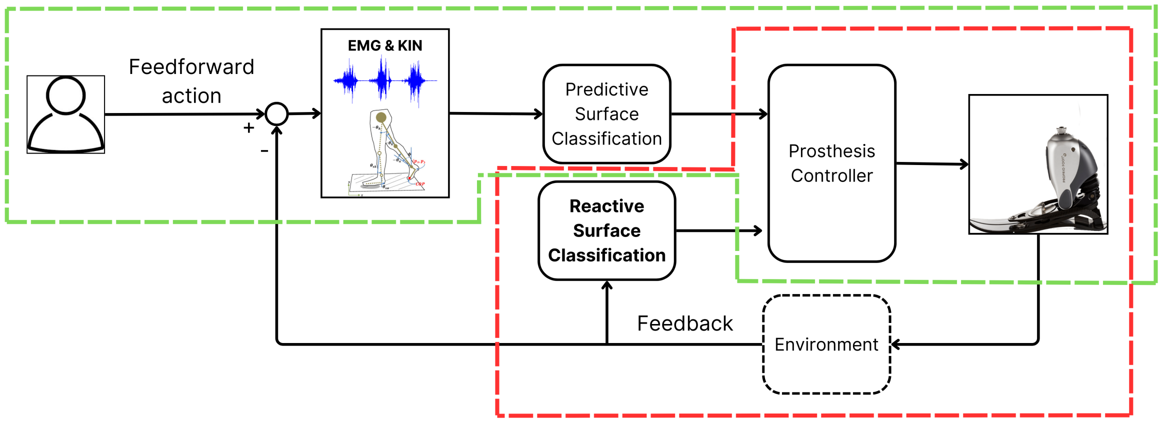

Fig. 1: Overview of the proposed research framework and its application on a robotic ankle-foot prosthesis that interacts with the human user and the environment. The green dashed line represents the anticipatory module of the proposed framework [8, 9]. The red dashed line represents the compensatory module discussed in detail in this work.

A. Experiment Protocol

1) Ruggedized Odyssey Ankle Prosthesis: For this study, the powered Ruggedized Odyssey Ankle (ROA) prosthesis (SpringActive, Inc) was used (see Fig. 2) [10, 11]. The ankle features a 250 W brushless DC motor connected in series with a 377 kN/m elastic spring, which transitions to a rigid carbon fiber foot. This design allows the spring to store and release elastic energy during the gait cycle, while the motor supplements any additional energy required. A motor encoder tracks the motor position, and an ankle encoder monitors the ankle angle. Additionally, an inertial measurement unit (IMU) is integrated within the casing above the ankle joint. The spring-generated ankle moment is estimated using a lookup table, developed by SpringActive, Inc., based on the motor position and ankle angle.

By default, the ROA prosthesis is controlled using a continuous phase-variable controller called the tibia controller (TC) [12]. The TC utilizes tibia kinematics to produce a reference motor trajectory that replicates the ankle angle patterns typically observed in the gait of healthy individuals without gait impairments. The TC has successfully been tested with individuals with transtibial (TT) LLA in walking and running activities on rigid terrain [12, 13]. However, the TC performance on bilaterally compliant terrain remains inferior to a recently proposed admittance controller (AC) [14], tailored for compliant surface walking.

2) Variable Stiffness Treadmill 2: The walking assessment of the recruited participants was performed using a specialized robotic platform developed by our lab, known as the Variable Stiffness Treadmill 2 (VST 2) [15] (see Fig. 2). The VST 2 can independently adjust the stiffness of both belts to simulate walking on compliant terrain. This experimental platform allows for the simulation of everyday walking conditions by recreating compliant surfaces and mimicking real-world stiffness scenarios in the lab.

3) Participant Data: Three healthy participants (two females, one male; age: 22 $\pm$ 1.73 years; height: 1.66 $\pm$ 0.03 m; weight: 58.98 $\pm$ 2.27 kg) completed walking trials on the VST 2 [15] wearing the ROA prosthesis. The prosthesis was attached via a carbon fiber bypass adapter on the left leg of the participants, preserving knee movement, while an adjustable shoe-lift (Evenup Corp., Buford, GA) was used on the right leg to compensate for height differences.

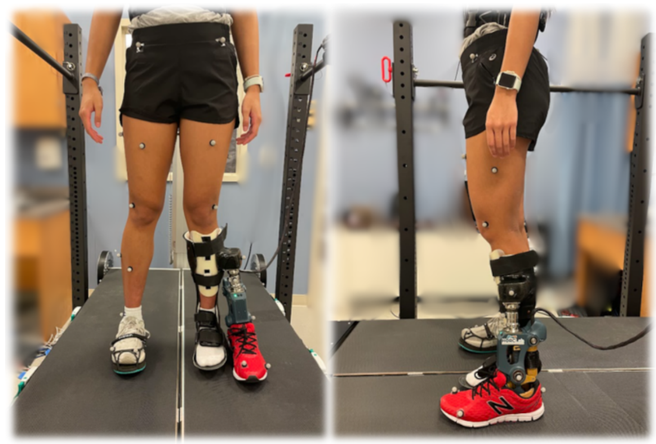

Fig. 2: Front and side view of a subject standing on the VST 2, while wearing the powered ankle-foot prosthesis Ruggedized Odyssey Ankle (ROA) attached to an ankle bypass adapter.

The study involved two sessions for training and data collection, respectively. During the training session, participants acclimated to the treadmill's stiffness levels without the prosthesis. They were then asked to identify a comfortable walking speed while using the prosthesis under rigid stiffness conditions. The independently selected comfortable walking speed was 0.65 m/s for all three study participants, which also reflects the preferred treadmill speeds previously reported by individuals with gait impairments (e.g., individuals with LLA or stroke survivors) [16]. Subsequently, participants performed short trials at that speed across rigid and compliant terrains, using the default controller (TC) of the ROA.

4) Data Acquisition: During the data collection session, participants completed walking trials at their self-selected comfortable speed. The first trial included walking for 200 gait cycles on a rigid surface using the TC. Subsequent trials included walking on bilaterally compliant terrain with stiffness levels mimicking rubber-on-foam (63 kN/m) and foam pads (25 kN/m), using the TC. Five-minute rest periods between trials were imposed to minimize participant fatigue. All participants provided written consent, and the presented experimental protocol was approved by the University of Delaware Institutional Review Board (IRB ID#: 1520622-8).

A motion capture system equipped with 8 cameras was used to collect kinematic data at 100 Hz (Vicon Motion Systems Ltd.). Additionally, the vertical Ground Reaction Force (GRF) response and the center of pressure (CoP) under each leg of the subjects was recorded at 65 Hz using a force sensor mat (Medical Sensor 3140TM, Tekscan, Inc., South Boston, MA) placed underneath both belts of the treadmill. Data from the prosthesis, such as ankle angle and moment, were recorded at a rate of 100 Hz.

B. Data Analysis

Based on previous works, it is safe to assume that the TC is the optimal controller for walking over rigid surfaces [12], while the AC performs better for walking tasks on compliant terrain [14]. This work aims to address the switch between the two controllers during transitions from rigid to compliant surfaces, aiding the rapid, real-time adaptation of the ROA to the new terrain. Considering that a natural human reflexive response takes place after a sensory stimulus (i.e. contact of the foot with a surface of different compliance), there is a reaction delay in the resulting compensatory response (i.e. adapting ankle stiffness to the new terrain). This reaction delay can be analogously compared to the time required to classify terrain stiffness upon contact with the ground and switch from a rigid ground controller (TC) to a compliant terrain controller (AC). During this time delay, the prosthesis controller remains set to its default setting for rigid surface walking. For this reason, this work will only focus on using trial data recorded using the default (TC) controller of the ROA. Additionally, it should be noted that since the focus of this study is concentrated on utilizing direct feedback from the ROA, the motion capture and force data will not be further analyzed within the scope of this work. From hereon, all data analysis will refer solely to the kinematic data captured by the ROA. Finally, analysis will be centered around classifying between the rigid (1000 kN/m) and the most compliant (25 kN/m) surface cases.

Data collected from the prosthesis included 22 quantifiable variables related to the prosthetic kinematics, including but not limited to ankle angle, ankle moment, IMU measurements, and gait parameters, such as gait progression and stride length among others. Kinematic data were sampled at 100Hz. Utilizing the prosthesis parameters, the ankle angular velocities were also derived as the time derivatives of the ankle angles. All kinematic data was then filtered via a 2nd order, low-pass Butterworth filter with a cut-off frequency of 5 Hz. Following the visual inspection of all prosthesis variables and comparing the average gait cycle data across the stiffness conditions of interest (1000 kN/m and 25 kN/m), we identified significant differences in the average values of several variables during the stance phase of gait. Statistical significance was calculated using an independent 2-sample t-test at the 95% confidence level and the selected variables included the ankle angle, ankle moment, IMU gyroscopic data (x-axis), and ankle angle velocity. Distinguishing between surface types during the first half of the gait cycle (i.e., the stance phase) was particularly critical, as surface identification in the latter half has minimal impact on user stability. This highlights the importance of focusing on early gait phases for effective terrain classification and stability enhancement.

Data were subsequently segmented into individual gait cycles and labeled according to terrain stiffness. These labeled data were then split into training (70%) and testing (30%) sets, with the training set used to develop machine learning classifiers capable of differentiating between rigid and compliant terrains and the testing set for real-time evaluation of the classification framework.

C. Classification Framework

1) Windowing Segmentation: A windowing segmentation analysis with non-overlapping windows was employed to preprocess the data for use as inputs to our classifier. Segmenting data into windows is a well-established practice in time-series analysis, as it enables the extraction of localized patterns and trends within specific intervals of the data [17]. Non-overlapping windows simplify computation by avoiding redundancy and ensuring that each segment contributes unique information to the model. This approach is particularly advantageous in gait analysis, where biomechanical variables such as ankle angle or moment evolve systematically over the gait cycle. By isolating discrete segments of the data, the classifier can more effectively learn distinct signals associated with different surface stiffness levels. Additionally, the segmentation process aligns with the natural periodicity of human locomotion, ensuring that inputs represent physiologically meaningful intervals.

For this reason, we utilized a windowing segmentation of 5 and 10 samples per window - corresponding to a window duration of 50 ms and 100 ms, respectively- to compare the effect of the window length in our classification strategy. The segmentation started at the beginning of the gait cycle – defined at heel-strike – and extended up to sample 60 ($\approx$ 50% of the gait cycle), resulting in a total of 12 or 6 windows, respectively, for the 50 and 100 ms windows. The windowing process was capped at 50% of the gait cycle, which corresponds to the late stance phase of gait, as decisions made after this point offer limited practical value for identifying transitions to compliant surfaces.

2) Support Vector Machine (SVM) Classifier: Our goal is to classify gait cycles into two class labels according to whether the transition happens on a (1) rigid or (2) compliant surface. We therefore analyzed the efficiency of different classification methods in identifying and classifying walking patterns related to compensatory reactions during early transitions between surfaces of variable stiffness.

Using MATLAB's Classification Learner, we evaluated various classifier types, including k-Nearest Neighbors (kNN), Linear Discriminant Analysis (LDA), Neural Networks (NN), and Support Vector Machines (SVM). While the results across kNN, Neural Networks, and SVM were similar, SVM generally outperformed the other models in terms of both accuracy and computational efficiency. For our SVM model, we utilized MATLAB's $fitcsvm$ function to train the SVM models on the provided dataset for each segmented window. To further enhance performance, we ran hyperparameter optimization for each window to determine the best parameters tailored to the specific characteristics of the data within that window.

3) Final Classification Decision: In this preliminary study, a total of 6 (or 12) decisions were made during the SVM classification phase, corresponding to the 100 ms (or 50 ms) segmented windows within the gait cycle. To derive a reliable classification outcome, a consensus-based approach was employed to consolidate these individual predictions into a single, final decision.

Specifically, the classifier confirmed its prediction if at least four (out of 6) or seven (out of 12) consecutive windows agreed on the outcome, prioritizing consistency in predictions over a simple majority vote. This method was chosen to leverage the temporal coherence of gait data, ensuring that decisions are based on stable trends rather than isolated predictions.

If consecutive agreement was not feasible, the final decision defaulted to the prediction of the last segmented window. This assumption rests on the premise that the later in the gait cycle a prediction is made, the more informative the classification inputs are likely to be.

4) Real-Time Testing and Framework Evaluation: A real-time simulation framework was designed to emulate the process of continuous data streaming from the ROA. The experimental data, gathered in the previously described controlled trials, were used offline to train the different classifiers. The partitioned test set data were then processed as if they were being streamed live from the prosthesis, simulating the conditions of real-time operation without the need to conduct new walking trials.

Specifically, data were simulated to arrive at a frequency of 100 Hz, replicating the actual sampling rate of the prosthesis sensors. The gait progression variable, a key output of the ROA, was used to detect heel-strike events, which served as markers to initiate the windowing segmentation outlined in earlier sections of this paper. To maintain robustness, a sliding buffer aggregated incoming data in chunks corresponding to the size of each window that was defined as 5 or 10 samples, equivalently 50 or 100 ms, per window. The segmented data windows were then filtered using a 2nd order, low-pass Butterworth filter (cut-off frequency of 5 Hz) to prepare them for classification, following the same processing pipelines as the training set data. Each window was passed sequentially to its respective trained classifier for real-time prediction. The distinct classifiers each provided a classification output that was then used to derive a conclusion about the stiffness of the terrain. A consensus-based decision-making process was used, in which a decision was finalized after achieving consistency across several consecutive outputs. This approach was aimed at mitigating the impact of transient noise or errors in individual predictions.

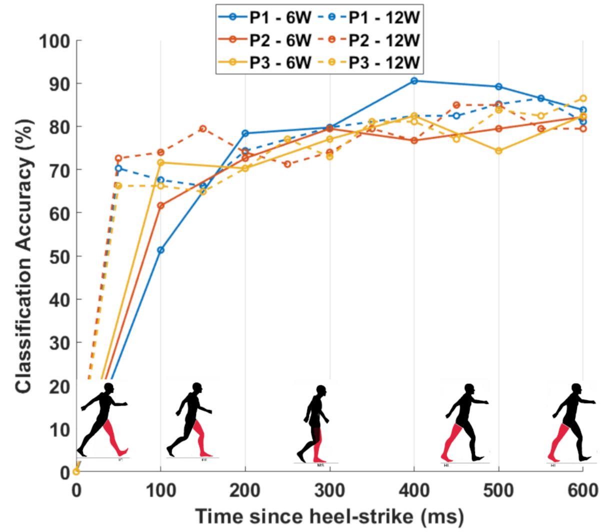

Fig. 3: Accuracy metric across participants (P1, P2, P3) using SVM window-classifiers within 600 ms of heel-strike. The solid lines represent the accuracy progression for the case of the 100 ms windows, corresponding to a segmentation of 6 Windows (6W). The dashed lines represent the accuracy progression for the case of the 50 ms windows, corresponding to a segmentation of 12 Windows (12W).

The performance of the framework was assessed by comparing predicted classifications with ground truth labels and the results were visualized using confusion charts. The framework was evaluated on a series of metrics based on the structure of a binary classification confusion matrix [18]. The metrics that were chosen to evaluate our model are briefly presented below.

- Accuracy: Proportion of true results (both Rigid and Compliant) in the data.
- Precision: A metric representing how many observations predicted as Compliant were in fact Compliant.
- Recall: A metric representing how many observations out of all Compliant observations have been classified as Compliant.
- F1-score: Harmonic mean between precision and recall. It ranges between 0 and 1, with 1 indicating perfect precision and recall.

Finally, the framework was evaluated not only on its accuracy, but also on how quickly decisions could be made following the detection of a heel-strike event, ensuring that the system's response time met the requirements for real-time prosthesis control. This simulation approach allowed for rigorous testing of the classifiers under conditions that closely mimic real-world prosthesis operation.

III. Results

A. Performance Comparison using 50 ms versus 100 ms Windows

In our comparison of the SVM classifier's performance with 50 ms and 100 ms window sizes, we found that a finer segmentation (50 ms) did not yield significant improvements

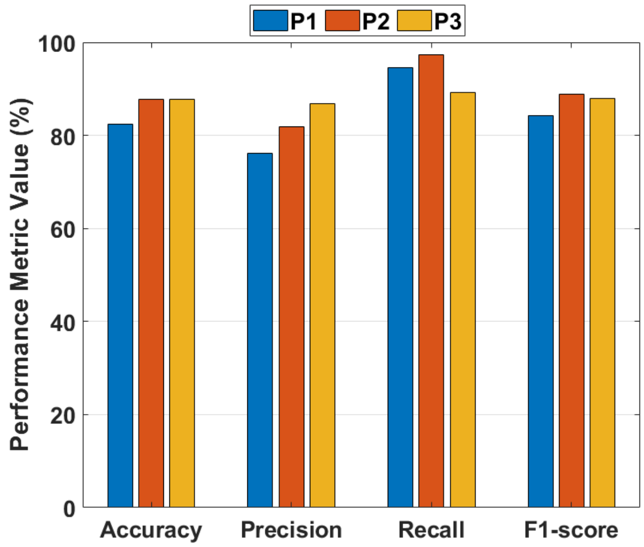

Fig. 4: Performance evaluation metrics across participants (P1, P2, P3) using SVM window-classifiers. The classification results depict the final decision metrics for the case of the 600 ms classification (decision taken at late stance phase) using a consensus-based decision process.

in classification metrics when compared to the 100 ms windows (see Fig. 3).

This can be attributed to the bandwidth limitations of the prosthesis, which constrain its ability to detect or respond to rapid changes within a 50 ms window. As a result, the signals extracted over shorter windows may not exhibit significant variability, leading to comparable classification outcomes between the 50 ms and 100 ms windows. Interestingly, classification accuracy was also observed to spike between 150 ms and 400 ms, highlighting the classifier's ability to make prompt and reliable decisions during the early and mid-stance phases of gait. This performance suggests that the 100 ms window allows enough time for the system to effectively adjust prosthesis parameters during these critical phases of walking.

B. SVM Classifier Performance

The performance of the proposed SVM-based binary classification framework demonstrates its ability to reliably distinguish between rigid and compliant surfaces with high accuracy and responsiveness within a short period of time after heel contact of the prosthesis with the ground. The detailed performance metrics for each participant are summarized in Fig. 4 for the full 600 ms. Across all participants, the SVM classifier consistently achieved high accuracy (82.4%–87.8%) along with strong precision, recall, and F1 scores. These results indicate that the classifier not only predicted surface compliance correctly in most cases but also maintained a balanced performance across true positives and false negatives, ensuring reliability in its decision-making. The high recall values should be noted, as they reflect the classifier's capacity to minimize misclassifications while ensuring accurate predictions of rigid and compliant surfaces.

Interestingly, looking at the precision scores of all participants, analysis of misclassified instances reveals a bias toward predicting rigid surfaces as compliant rather than the reverse. This behavior is advantageous in practical applications, as it prioritizes safety by ensuring that the prosthesis errs on the side of caution. Misclassifying a compliant surface as rigid could result in insufficient adjustments, potentially leading to instability or falls. In contrast, treating a rigid surface as compliant poses a lower risk, as the prosthesis would still be able to provide the required support to walk on a rigid terrain, ensuring a sub-optimal, yet stable gait [14].

By reliably distinguishing between rigid and compliant surfaces and prioritizing safety in its classification biases, the framework offers a reactive approach to terrain adaptation.

C. Classification Timing and Implications for Real-Time Prosthetic Control

The consensus-based approach demonstrated the ability to provide reliable predictions for the majority of gait cycles by the time we reached window 4, eliminating the need to wait through all 6 windows. This early decision-making process highlights the potential of leveraging such techniques to enhance the robustness of the final prediction. As shown in Fig. 5, which illustrates the number of correctly classified gait cycles versus misclassifications across all participants, the majority of gait cycles were accurately predicted by the time window 4 (W4) was reached (i.e., when 4 consecutive identical predictions occurred). Misclassifications were minimal, especially for participants P1 and P2. For participant P3, predictions were more evenly distributed across windows 4 (W4), 5 (W5), and 6 (W6), with a comparable number of misclassifications occurring in W4 and W6. These findings demonstrate the promising potential of using data from the early stance phase of gait for accurate terrain classification, thus underscoring the ability of our system to make reliable decisions early in the gait cycle. However, the consensus-based approach introduces some practical limitations, as alternative methods — such as probabilistic models or confidence-weighted voting — could potentially provide more robust and nuanced final decisions. Future work will explore these possibilities to improve the reliability, adaptability, and speed of the classification process.

IV. Discussion

The proposed reactive control framework demonstrates promise in adapting robotic prostheses to varying terrain conditions. However, some limitations need to be addressed. Specifically, this study was conducted at a fixed walking speed, so future work will investigate how the framework performs across different speeds to improve its adaptability. While the classification response time closely aligns with the average human reaction times reported previously in the literature [19], further optimization is needed to enhance real-time performance. Adaptive control strategies could refine reaction times, making prosthetic adjustments even more seamless. Additionally, the current approach differentiates only between rigid and one level of compliant surfaces.

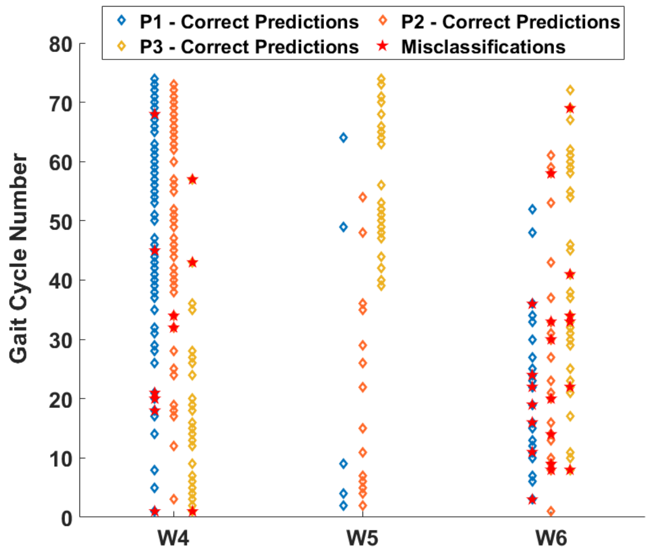

Fig. 5: Final classification prediction across participants (P1, P2, P3) per tested gait cycle following a consensus-based decision process for the case of the 600 ms classification. W4, W5, and W6 correspond to the segmented windows 4,5, and 6.

Expanding classification to intermediate stiffness levels will improve real-world applicability, while integration into a closed-loop prosthetic system and validation through testing on individuals with TT LLA remain crucial next steps. These efforts will refine the framework, making it more robust for everyday prosthetic use.

V. Conclusion

This paper introduces the first reactive controller framework using SVM-based classification to adaptively adjust robotic prosthesis ankle stiffness in response to surface compliance changes. The proposed framework incorporates kinematic data from a robotic ankle-foot prosthesis, enabling real-time classification of surface stiffness upon 400 ms after initial foot-ground contact. The SVM-based classifier demonstrated reliable performance in distinguishing between rigid and compliant surfaces, achieving an accuracy of up to 88%. This ability to classify surface compliance in real-time utilizing direct feedback from the prosthesis allows for adaptive control strategies that dynamically tune the prosthesis's parameters during locomotion. The integration of this reactive control mechanism into a high-level prosthetic system could enable reactive adjustments, enhancing both the stability and adaptability of prosthetics and wearables during transitions from rigid to compliant surfaces.

The results of this study are particularly significant as they underline the feasibility of using machine learning-driven classification to inform real-time control in lower-limb prosthetics. This approach paves the way for advanced prosthetic and wearable devices that consider human-robot interaction as a holistic system, where both human and robotic feedback play a critical role in optimizing performance.

VI. Acknowledgments

We sincerely thank Dr. Chrysostomos Karakasis for generously providing the experimental data used in this study.

References

[1] B. J. Hafner, S. J. Morgan, D. C. Abrahamson, and D. Amtmann, "Characterizing mobility from the prosthetic limb user's perspective: Use of focus groups to guide development of the prosthetic limb users survey of mobility," *Prosthetics and Orthotics International*, vol. 40, pp. 582–590, 10 2016.

[2] M. E. V. D. Berg, C. J. Barr, S. Cavenett, and M. Crotty, "Gait analysis in individuals with transtibial amputation walking on sand: Comparing everyday prosthesis with a water-activity prosthesis," *Prosthetics and Orthotics International*, vol. 32, pp. 107–115, 4 2020.

[3] J. Kim, M. J. Major, B. Hafner, and A. Sawers, "Frequency and circumstances of falls reported by ambulatory unilateral lower limb prosthesis users: A secondary analysis," *Physical Medicine and Rehabilitation*, vol. 11, pp. 344–353, 4 2019.

[4] D. Quintero, A. E. Martin, and R. D. Gregg, "Toward unified control of a powered prosthetic leg: A simulation study," *IEEE transactions on control systems technology : a publication of the IEEE Control Systems Society*, vol. 26, pp. 305–312, 1 2018.

[5] S. Cheng, C. A. Laubscher, and R. D. Gregg, "Controlling powered prosthesis kinematics over continuous transitions between walk and stair ascent," pp. 2108–2115, 12 2023.

[6] J. Mendez, S. Hood, A. Gunnel, and T. Lenzi, "Indirect volitional swing control allows for level-ground walking and crossing over obstacles with a powered knee and ankle prosthesis," *Science robotics*, vol. 5, p. eaba6635, 7 2020.

[7] K. Ghonasgi, T. Higgins, M. E. Huber, and M. K. O'Malley, "Crucial hurdles to achieving human-robot harmony," *Science Robotics*, vol. 9, 11 2024.

[8] C. Angelidou and P. Artemiadis, "On predicting transitions to compliant surfaces in human gait via neural and kinematic signals," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 2214–2223, 2023.

[9] C. Angelidou and P. Artemiadis, "On intuitive control of ankle-foot prostheses: A sensor fusion-based algorithm for real-time prediction of transitions to compliant surfaces," *IEEE International Conference on Intelligent Robots and Systems*, pp. 2122–2127, 2023.

[10] M. Grimmer, M. Holgate, J. Ward, A. Boehler, and A. Seyfarth, "Feasibility study of transtibial amputee walking using a powered prosthetic foot," *International Conference on Rehabilitation Robotics*, pp. 1118–1123, 8 2017.

[11] J. Ward, K. Schroeder, D. Vehon, R. Holgate, A. Boehler, and M. Grimmer, "A rugged microprocessor controlled ankle-foot prosthesis for running," in *in 39th annual meeting of the american society of biomechanics (ASB)*, 08 2015.

[12] M. A. Holgate, T. G. Sugar, and A. W. Bohler, "A novel control algorithm for wearable robotics using phase plane invariants," *Proceedings - IEEE International Conference on Robotics and Automation*, pp. 3845–3850, 11 2009.

[13] J. Ward, K. Schroeder, D. Vehon, R. Holgate, A. Boehler, and M. Grimmer, "A rugged microprocessor controlled ankle-foot prosthesis for running," 08 2015.

[14] C. Karakasis, R. Salati, and P. Artemiadis, "Adjusting the quasi-stiffness of an ankle-foot prosthesis improves walking stability during locomotion over compliant terrain," *IEEE International Conference on Intelligent Robots and Systems*, pp. 2140–2145, 2023.

[15] V. Chambers, B. Hobbs, W. Gaither, Z. Thé, A. Zhou, C. Karakasis, and P. Artemiadis, "The variable stiffness treadmill 2: Development and validation of a unique tool to investigate locomotion on compliant terrains," *Journal of Mechanisms and Robotics*, vol. 17, 3 2025.

[16] C. E. Capó-Lugo, C. H. Mullens, and D. A. Brown, "Maximum walking speeds obtained using treadmill and overground robot system in persons with post-stroke hemiplegia," *Journal of NeuroEngineering and Rehabilitation*, vol. 9, pp. 1–14, 10 2012.

[17] G. Wang, Q. Li, L. Wang, W. Wang, M. Wu, and T. Liu, "Impact of sliding window length in indoor human motion modes and pose pattern recognition based on smartphone sensors," *Sensors 2018, Vol. 18, Page 1965*, vol. 18, p. 1965, 6 2018.

[18] M. Shirdel, M. D. Mauro, and A. Liotta, "Worthiness benchmark: A novel concept for analyzing binary classification evaluation metrics," *Information Sciences*, vol. 678, p. 120882, 9 2024.

[19] A. Jain, R. Bansal, A. Kumar, and K. Singh, "A comparative study of visual and auditory reaction times on the basis of gender and physical activity levels of medical first year students," *International Journal of Applied and Basic Medical Research*, vol. 5, p. 124, 2015.