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Machine Learning-Based Gait Mode Prediction for Hybrid Knee Prosthesis Control

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Abstract— **Recently, hybrid prosthetic knees, which can combine the advantages of passive and active prosthetic knees, have been proposed for individuals with a transfemoral amputation. Users could potentially take advantage of the passive knee mechanics during walking and the active power generation during stair ascent. One challenge in controlling the hybrid knees is accurate gait mode prediction for seamless transitions between passive and active modes. However, data imbalance between passive and active modes may impact the performance of a classifier. In this study, we used a dataset collected from nine individuals with a unilateral transfemoral amputation as they ambulated over level ground, inclines, and stairs. We evaluated several machine learning-based classifiers on the prediction of passive (level-ground walking, incline walking, descending stairs, and donning and doffing the prosthesis) and active mode (ascending stairs). In addition, we developed a generative adversarial network (GAN) to create synthetic data for improving classification performance. The results indicated that linear discriminant analysis and random forest might be the best classifiers regarding sensitivity to the active mode and overall accuracy, respectively. Further, we demonstrated that using the GAN-based synthetic data for training improves the sensitivity of classifiers.**

I. INTRODUCTION

The goal of prosthetic devices is to restore functional mobility for amputee patients. For individuals with a transfemoral amputation, the wide variety of prosthetic knees generally can be categorized into three types: passive, active, and hybrid knees. Passive prosthetic knees [1] mainly contain hydraulic or pneumatic passive components to adjust the resistances of knees for ambulation. While these passive devices account for nearly all commercially available knees on the market, they cannot provide additional energy to users; users often have difficulty with energy-demanding activities, such as stair ascent or sit-to-stand. Active (powered) prosthetic knees [2], [3], [4], [5] contains actuators to control joints. Actuating joints facilitate energy-demanding ambulation with a reciprocal gait. However, often the benefits of passive mechanics are lost with these active devices and the complexity of the control system often is increased as more activities are restored. In addition, motor components and additional components related to their driving, such as a battery, increase the weight and costs of the knees.

Recently, hybrid knees [6], [7], [8], capable of active and passive control, have been proposed. These types of knees take advantage of properties of both passive and active knees. The passive mechanism is often controlled by a microprocessor which adjusts the resistance of the prosthesis through stance and swing phase to allow natural gaits. On the other hand, the active mechanism can be engaged to control the knee only when performing energy-demanding ambulation. Hybrid knee devices have the potential to consume less battery power since energy is only required for a limited number of activities; the passive component is engaged for the majority of ambulation. Depending on the control architecture, hybrid knees have the potential to decrease control complexity compared with fully active knees. In addition, the weight or size of the system likely can be reduced.

One of the challenges in controlling hybrid knees is to allow intuitive and seamless transitions between the passive and active modes. Correct prediction of active mode could allow a user to take advantage of passive dynamics during walking but then seamlessly transition to active control for climbing stairs with a reciprocal gait thereby likely lowering user burden.

For fully active devices, various machine learning-based classifiers have been proposed to predict ambulation modes. For example, Linear Discriminant Analysis (LDA) [9] is a well-known method that has been used to predict transitions between level walking, incline walking, and stairs. A Gaussian mixture model [10] has also been proposed to classify ambulation modes, including standing, sitting, and walking. Recently, neural network-based prediction methods have been proposed as well, such as using surface electromyography and inertial measurement unit data to predict gait mode transition between level-ground walking and incline walking using a multilayer perceptron [11], and using convolutional neural networks for depth sensor-based prediction [12] of mode transition between level-ground walking and various locomotion modes, including ascending/descending stairs and incline walking, as well as vice versa. For hybrid devices, a classifier may have difficulty identifying the active mode because likely passive and active modes are not represented equally. In other words, the amount of ambulation for passive and active modes is imbalanced during the course of an average user's day. Most ambulation activities during daily living can be accomplished with a passive knee

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(e.g., level-ground walking or descending stairs). Active mode for ambulation activities that require power generation at the knee represent a much smaller portion of the user's day (e.g., climbing stairs). These aspects may affect the balance of data collected as well as predictive performance. Although various gait mode predictors have been proposed, it is not currently known which classification techniques can best predict between passive and active modes for hybrid control.

This study focused on evaluating several general machine learning classifiers for hybrid knee control. In addition, as a preliminary step to overcome the imbalance between the amount of data between passive and active modes, we propose a generative adversarial network (GAN)-based data augmentation to improve the performance, especially in terms of sensitivity to the active mode. Nine individuals with a transfemoral amputation performed ambulation activities using pre-developed state machine-based controller [13] including level-ground walking, incline walking, descending stairs, and donning and doffing the prosthesis as passive mode and ascending stairs in active mode. Gait mode prediction was evaluated via an offline analysis. Our testing results indicated that LDA is adequate for gait mode prediction of hybrid prosthetic knees, and GAN-based data augmentation has the potential to improve the sensitivity of classifiers to the active mode.

II. Methods

A. A hybrid knee prosthesis

We used a lightweight hybrid knee [6]; the details are described in [6] and [13]. The control system is based on a finite state machine, as shown in Fig. 1.

In the passive control, a variable and tunable electronic brake adjusted resistance. The passive controller was used for passive walking (PW) modes: level-ground walking, incline walking, descending stairs, and donning and doffing the prosthesis.

In active control, an impedance controller has been implemented [13], [14], according to the following equation:

$$\tau = -k(\theta - \theta^{eq}) - b\dot{\theta} \tag{1}$$

where τ represents the joint torque, θ and $\dot{\theta}$ represent the knee angle and velocity, respectively, and k, b, and θ^{eq} denote the stiffness, damping coefficient, and equilibrium angle, respectively. These three impedance parameters (i.e., stiffness, damping coefficient, and equilibrium angle) for stair ascent (SA mode) were tuned for each user.

B. Data collection

Nine individuals with a transfemoral amputation participated in this study. This study was approved by Northwestern University Institutional Review Board, and participants provided written informed consent. Each participant was fit to the hybrid knee and an Ossur Low Profile Vari-flex foot.

A data collection protocol is the same as our previous work [13]. The impedance parameters in finite state machines for active control were tuned for each user [14], and the amount of resistance during passive control was tuned for each state. Transitions between PW and SA modes were controlled via a key fob and occurred at toe-off.

The users performed 10 trials of level-ground walking, ascending/descending inclines, ascending/descending stairs, and donning/doffing the prosthesis. Ambulation during level-walking, inclines, descending stairs and donning/doffing were not classified but rather grouped together as PW modes. Only stair ascent was considered as the active mode (i.e., SA mode).

During data collection, data from sensors embedded in the hybrid knee, including a six-axis load cell, 3-axis acceleration, 3-axis gyroscope, lower limb joint angles (thigh, and shank angles), knee position and velocity, and requested and actual knee motor currents, were continuously collected at 125 Hz. Then, we extracted six features per sensor data, including initial, final, minimum, maximum, mean values, and standard deviation, from the 300 ms windows that started 275 ms prior to toe-off and ended 25 ms after toe-off, based on our previous work [15]. Therefore, all 108 features were extracted for every toe-off and subsequently scaled from -1 to 1. The number of data per user is shown in Table I.

TABLE I: The number of steps in each gait modes per user.

User	PW mode	SA mode
TF1	1078	42
TF2	1268	51
TF3	757	48
TF4	1255	41
TF5	963	60
TF6	1094	69
TF7	816	46
TF8	715	36
TF9	870	73
All	8816	466

C. Software

This study used Scikit-Learn (v. 1.1.3) and TensorFlow (v. 2.8.0) libraries in Python (v. 3.9) on a laptop (Nitro 5, Acer) with Windows 11, an NVIDIA GeForce RTX 3050Ti Laptop GPU, and 32GB DDR4 RAM.

1) Machine learning classifiers: We used general machine learning classifiers available in Scikit-Learn with default values for the algorithm parameters: LDA, Support Vector Machine (SVM), Random Forest (RF), Quadratic Discriminant Analysis (QDA), Decision Tree (Tree), and Gaussian Process (GP).

2) Data augmentation: We adopted generic structures of deep convolutional GANs [16] for data augmentation. The overall flow is described in Fig. 2.

A one-dimensional sensor data array of size 108 was reshaped to a two-dimensional matrix of size 18 by 6 to train the proposed GAN model (i.e., outputs of the generator and inputs to the discriminator).

The input data to the generator was an array of size 100, and it was produced randomly every epoch. The Input values from index 0 to 9 were set to -1 if the corresponding class of

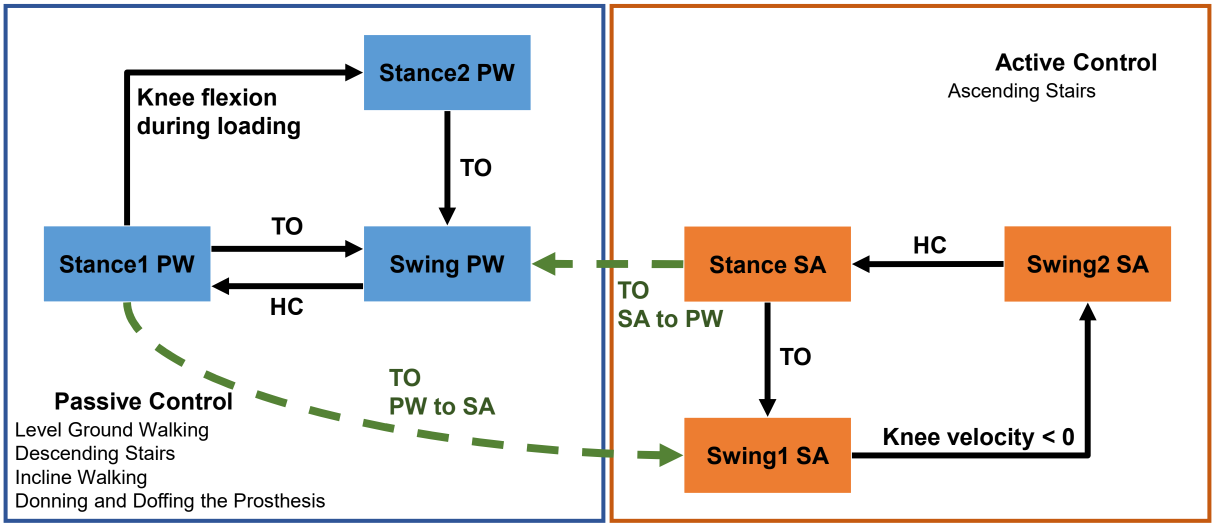


Fig. 1: Finite state machine-based hybrid control. In passive control (PW), an electronic brake controlled the amount of resistance for each state. In active control (SA), an impedance controller has been implemented. The transitions between passive and active modes (green dashed lines) were controlled via a key fob. Here, TO and HC represent toe-off and heel contact, respectively.

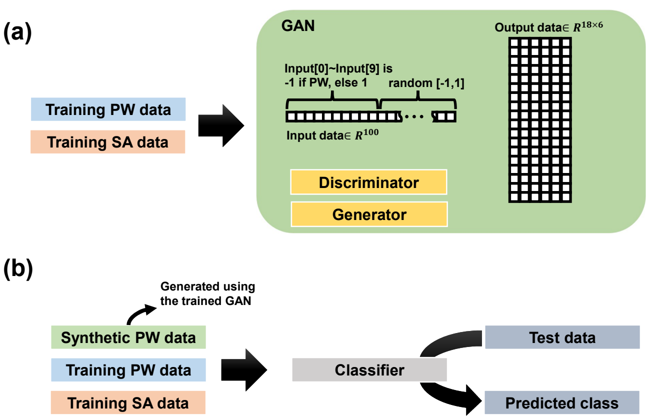


Fig. 2: GAN-based data augmentation. (a) Sensor data were reshaped for use as output data in the GAN. During the training, the generator produced output data (i.e., synthetic sensor data) from random noise. (b) Although both PW and SA data were used to train the GAN, only the synthetic PW data were used to train classifiers.

the output sensor data was PW mode and 1 otherwise. The input values in the remaining indexes were random values from -1 to 1.

The discriminator consists of:

Input-Fl-D54-D9-D1 (Output)

The generator consists of:

Input-d864-r(18,6,8)-C4-BN-C2-BN-c1 (Output)

Here, Fl denotes a flattening layer, Dk denotes a dense layer of k units with no activation function, dk denotes a dense layer of k units with Leaky Rectified Linear Unit (LeakyReLU) activation, r(x,y,z) denotes a reshaping layer that reshapes inputs into the x, y, z shape, Ck denotes a transposed two-dimensional convolution layer with k filters with LeakyReLU, BN denotes batch normalization, and ck denotes a transposed two-dimensional convolution layer with k filters with hyperbolic tangent activation. All convolution layers have the same padding, kernel size of (5, 5), stride length of (1, 1), and with no bias vector.

The GAN was trained for 20 epochs (a batch size of 128, ADAM with a learning rate of 0.001). The training time for the GAN was about 5 minutes per user.

After training, synthetic PW data were generated; the number of synthetic data was the same as that of original PW training data. Then, classifiers were trained on the original training data and synthetic PW data.

D. *Evaluation*

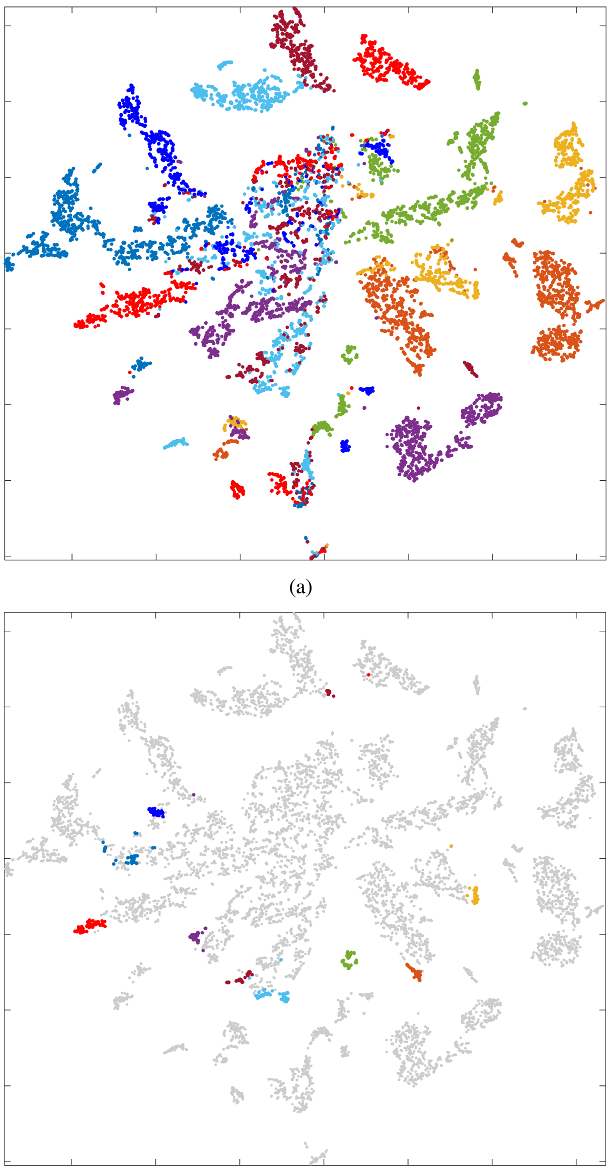
Sensitivity to SA mode and overall accuracy were calculated in order to evaluate the classifiers. Accuracy indicates the ratio between the number of all correct predictions and the total number of all data; sensitivity to SA mode indicates the ratio between the number of correct predictions of SA and the total number of SA data. Sensitivity represents whether a classifier can predict SA motion without missing the transition when a user wants to climb stairs.

Leave-one-out cross-validation was used to calculate classification accuracy and sensitivity. In other words, classifiers were trained on eight users and applied to the remaining user. A paired sample t-test was used to evaluate improvement by data augmentation.

III. Results

A. *Data distribution*

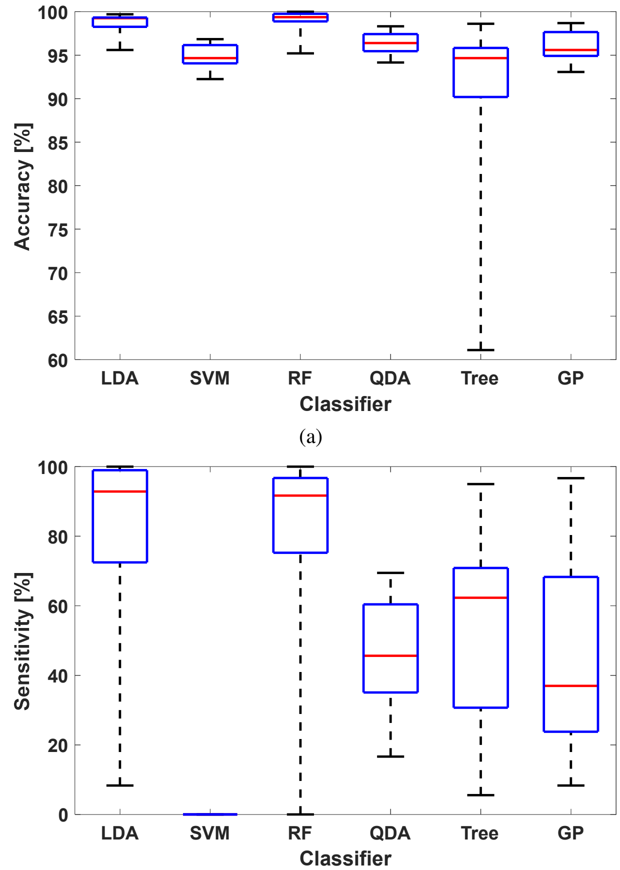
The collected sensor data were visualized using t-distributed stochastic neighbor embedding (t-SNE), as shown in Fig. 3. All data were not easily distinguished



(a)

(b)

Fig. 3: Data visualization using t-SNE. Color represents each user for all ambulation modes (a) and SA only (b). SA data had large variability across users.



(a)

(b)

Fig. 4: Performance in terms of accuracy (a) and sensitivity (b). LDA, SVM, RF, QDA, Tree, and GP showed the average accuracy of 98.7%, 94.8%, 98.9%, 96.4%, 90.0%, and 96.0%, and the average sensitivity of 80.7%, 0.0%, 77.8%, 46.3%, 54.0%, and 47.8%, respectively. In each bar plot, a red line represents the median, a blue box represents the 25th and 75th percentiles, and black lines represent the range between minimum to maximum.

across users. However, the SA data from one user were grouped, and they were separated from those of other users.

B. Evaluation of classifiers

Fig. 4 shows the evaluation of the machine learning classifiers in terms of accuracy and sensitivity. LDA and RF showed higher average accuracy of 98.7% and 98.9%, respectively. However, sensitivity was significantly lower than accuracy; the average sensitivity of LDA and RF was only 80.7% and 77.8%, respectively. As the worst case, SVM showed 0% sensitivity. In other words, SVM was not able to detect SA mode.

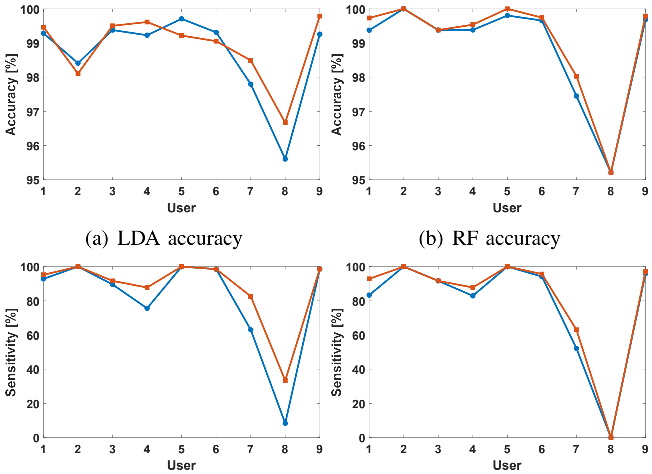
C. Evaluation of GAN-based data augmentation

For data augmentation, only LDA and RF were evaluated among the machine learning classifiers because they outperformed other classifiers.

Generally, the classifiers trained on augmented data showed slightly better performance than those trained on original data (Fig. 5); the performance of both LDA ($p < 0.001$) and RF ($p = 0.008$) with data augmentation were significantly different from that without data augmentation. In the case of LDA, average accuracy and sensitivity increased from 98.7% to 98.9% and from 80.7% to 87.5%, respectively. In the case of RF, average accuracy and sensitivity increased from 98.9% to 99.0% and from 77.8% to 80.9%, respectively.

IV. Discussion

This study aims to perform binary classification between passive and active modes. Although the task is not very



(a) LDA accuracy (b) RF accuracy

(c) LDA sensitivity (d) RF sensitivity

Fig. 5: Performance improvement using the GAN in terms of accuracy (a)-(b) and sensitivity (c)-(d). Blue and orange lines indicate the performance without and with data augmentation, respectively. GAN-based augmented data improved classification performance, except for the TF2, TF5, and TF6, in terms of the accuracy of LDA.

complex, performance significantly varies according to classifiers. We believe the reason for this is that the amount of PW and SA data is imbalanced. Additionally, each user's SA data is grouped and separated from others. Despite this increased difficulty in across-user classification, GAN-based data augmentation improved performance, particularly in terms of sensitivity. Because of differences in user characteristics, classifiers are usually trained with each user's own data [17]. If a GAN can generate reliable synthetic data for new users using data from other users, the practicality will be improved as new users will not have to spend time collecting their own data for classifier adaptation.

Among six general machine learning classifiers, LDA and RF outperformed. LDA and RF were good in terms of sensitivity and accuracy, respectively. LDA would be the best classifier for gait mode prediction because the high computation costs of RF hinder real-time processing.

There were considerable differences in accuracy and sensitivity (Fig. 4). Although the proposed GAN was trained on both PW and SA data, only the synthetic PW data were used to train the classifiers. This is because performance decreased when synthetic SA data were used. We speculate that SA for one user cannot be easily predicted using SA data from different users as they were not grouped (Fig. 3). Interestingly, despite these difficulties, LDA performed better than nonlinear classifiers, such as QDA or GP.

The GAN did not always improve the prediction performance. The LDA trained on augmented data showed worse accuracy than that trained on original data in the case of TF2, TF5, and TF6. During training, in lower epochs, the GANs for these users showed better performance. However, the performance was not maintained. We believe the performance of GANs could be improved by adjusting network structures or parameters, which were heuristically chosen in this study. For example, a generator with loss considering the Mahalanobis distance between the generated data and distributions of the original data may improve the performance.

The user TF8 showed poor sensitivity compared to the other users. We performed leave-one-out cross-validation using an LDA classifier leaving out TF8 (not shown in the Results section). The average sensitivity of 89.9% was not significantly different ($p = 0.077$) from that trained including TF8 (89.8%, Fig. 4(b)). These results suggest that TF8 may have different characteristics from the other users. Therefore, further research is necessary to investigate the influence of user characteristics, such as experience, K level, prosthetic leg side, or weight, on data augmentation and classification. Grouping users based on characteristics may provide more reliable synthetic data for a user within the group.

V. Conclusion

This study compared six machine learning classifiers to predict gait mode for hybrid knee prosthesis control. LDA and RF were the best classifiers in terms of accuracy and sensitivity.

In addition, data augmentation using a GAN was proposed to overcome the data imbalance between the amount of data in PW and SA modes. The results indicate that data augmentation improves performance in terms of sensitivity.

In conclusion, LDA and RF might be adequate for gait mode prediction for a hybrid knee system; data augmentation may overcome data imbalance problems between passive and active modes.

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