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Continuous and Unified Modeling of Joint Kinematics for Multiple Activities

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ABSTRACT Intuitive control of powered prosthetic lower limbs is still an open-ended research goal. Current controllers employ discrete locomotion modes for well-defined and frequently encountered scenarios such as stair ascent, stair descent, or ramps. Non-standard movements such as **side-shuffling into cars and avoiding obstacles** are challenging to powered limb users. Human locomotion is a continuous motion comprising rhythmic and non-rhythmic movements, fluidly adapting to the environment. It exhibits strong inter-joint coordination and the movement of a single joint can be largely predicted based on the movement of the rest of the body. We explore a continuous and unified kinematics estimation strategy for a wide variety of movements without the need for labeled examples. Our data-driven approach uses natural body motion from the intact limbs and trunk to generate a kinematic reference trajectory for prosthetic joints. Wearable sensors were worn by 63 subjects without disabilities to record full-body kinematics during typical scenarios (flat ground and stairs), and non-rhythmic and atypical movements (side shuffles, weaving through cones, backward walking). A Recurrent Neural Network (RNN) was trained to predict right ankle and knee kinematics from the kinematics of other joints as inputs. Results were assessed on 3 different test subjects previously unseen by the network. All predictions had a RMSE of less than 7.5 degrees and a high correlation across activities. These offline predictions were robust to subject-specific variations such as walking speed and step length. Additionally, to test the feasibility of using a data-driven reference towards prosthetic control in real-time, a systems test was designed with a single participant. The controller acquired live kinematics, generated predictions using a pre-trained neural network, and demonstrated the capability to actuate the knee joint of a powered prosthesis for the treadmill walking task.

INDEX TERMS Prosthetic limbs, biomechatronics, rehabilitation robotics.

I. INTRODUCTION

Powered limbs are getting more and more capable in their hardware capacity [1], [2]. The new devices are lighter and more powerful with multiple joints and degrees of freedom. However, given the vast space of possible movements, intuitive control of powered limbs is still challenging, especially for multiple joints [3]. We demonstrate here a single unified controller for a range of rhythmic and non-rhythmic activities including the transitions in between.

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Normative kinematic data were collected from subjects with no amputations. This dataset was used to train a data-driven controller to predict the reference trajectories of ankle and knee prosthetic joints. In short, the coordination of the entire body is exploited to produce desirable kinematic targets for the prosthetic limb.

A. CONTROL BY CLASSIFICATION OF ACTIVITIES AND GAIT PHASES

The most commonly encountered terrains and activities such as flatground walking, stair ascent, etc. have been successfully addressed in modern prostheses by categorization of control into a handful of ''locomotion or activity mode'' [4]–[6].

At this stage, unstructured activities that require unique non-repeated movements such as sports, getting in and out of cars or restaurant booths, obstacle avoidance, and navigating uneven terrain are challenging as they do not cleanly correspond to commonly-used control modes [7], [8]. Moreover, with most walking bouts lasting less than 30 seconds [9], mode transitions are common. Consequently, active users often prefer passive devices for their simplicity while adopting compensatory movements which can be physically demanding and detrimental [10], [11].

A possible solution could be to define more modes to encompass more types of activities. This requires the construction of more mode-specific controllers and makes the task of choosing the 'right' mode more difficult and error-prone [12].

Another potential limitation on expanding the number of modes is the tuning of the control parameters which go with it. In current mode-based control, the gait cycle within a mode is divided into phases (swing, stance), each with distinct controllers and control parameters requiring hours of tuning [13]. This phase-based control strategy transitions between gait phases, *within* a mode using a finite state machine approach [12]. Each state uses a set of static parameters that are hard-coded into the controller. The number of tuneable variables rapidly increases with the number of parameters per control law, the number of states per activity, the number of activity modes, and the number of joints to be actuated. This has led to several independent studies exploring strategies to reduce tuneable parameters [14], or automatically tune these parameters using methods such reinforcement learning [15], [16].

This strategy has difficulty handling abrupt mid-phase changes in activities [12]. Each gait cycle must begin with the particular gait phase (e.g heel-strike). Huang *et al.* [17] mitigated this problem by training multiple gait phase-dependent classifiers for a continuous mode classification and using an insole pressure sensor to detect the current phase. This strategy mandates a cyclic progression through the gait phase. This limits its flexibility to accommodate irregular or unprogrammed gait patterns, e.g. walking in a crowd or over rocky ground, and unexpected events such as tripping.

B. EXPLOITING WHOLE-BODY COORDINATION FOR CONTINUOUS CONTROL

Another approach is to rely on the strong inter-joint coordination exhibited by humans during locomotion [3], [13], [18], [19]. This coordination of the whole body means that movements of any one joint are highly correlated with the movement of the rest of the body. The trajectory of movements of the intact limbs provides the means to estimate the movement of the missing limb with a high likeness to observed behavior. This observation also motivates our Coordinated Movement (CM) controller which will be described in the following subsection.

An early approach called echo control replayed or ''echoed'' the movement of the sound leg on the prosthetic limb [20]. However, this delayed playback failed when asymmetric movements were desired and required the sound leg to lead all movements.

Complementary Limb Motion Estimation (CLME) infers the intended motion of affected limbs from the motion of the residual limbs and maps this to a reference trajectory for robotic prosthetic joints to track [18]. The mapping is derived through regression of physiological gait recordings of subjects with no disability and was evaluated on rhythmic activities of flatground walking and stair ambulation.

As opposed to mode-based EMG control, direct EMG control uses active and continuous input from the human user muscle activity to determine prosthesis dynamics. Direct EMG control mimics the biological neural control pathway and provides intuitive coordination with the prosthesis. It has the potential to not be constrained to rhythmic locomotor tasks. Recent studies have explored controlling joint position and torque, however current evidence is mostly limited to target reaching tasks [21], [22] or well-defined movements such treadmill walking, postural control, sitting, stair climb [23]–[27].

A more recent success uses virtual constraints to define joint trajectories as functions of a monotonic phase variable that continuously represents the gait cycle across the entire stride [13]. By learning the holonomic mapping from thigh angle to foot position, the amputee user has more agency over the timing and position of the prosthetic joint patterns, allowing for atypical activities such as backward walking and walking over obstacles [3]. This strategy has fewer parameters to tune but still relies on several hard-coded phase variable values to detect and progress through the gait phases. Moreover, mapping a phase variable to normative flatground walking restricts the possible atypical non-rhythmic activities to those that are kinematically similar to flatground walking.

These strategies are 'continuous' in that they do not divide the gait cycle into sub-phases. They reduce the burden of tuning parameters, but do not easily accommodate different modes or activities. Each movement class requires tuning of specific parameters [3], [18] separately. We aim to build on these approaches to provide continuous control, even across different types of activities.

C. MACHINE LEARNING IN PROSTHETIC CONTROL

Advanced prosthetic control applies machine learning for classification of input sensor signals (EMG and mechanical) into discrete locomotion modes. The algorithms explored, such as linear discriminant analysis (LDA), support vectors machine (SVM), [17] are suitable for partitioning the total movement space into limited and finite movement classes. This process of classification requires labeling of the input data with corresponding classes or locomotion modes, with each class or mode characterized by a predefined movement profile or trajectory.

Recently, visual data was used for the classification of the environment into 3 to 5 locomotion modes [28], [29]. This is a promising frontier towards adding redundancy and robustness to the overall system by acquiring direct information about the current and upcoming environment rather than relying purely on user cues [12]. However, as with all classification tasks, the process of labeling has been known to be resource-intensive and fraught with subjectivity [30], [31]. Along with classification, machine learning is suitable for regression tasks and has been explored towards prosthesis control as well. CLME [18] uses linear regression to continuously determine prosthetic joint positions. The regression method is suggested to be better suited for adapting the controller to varying walking speeds [19]. The authors explored Gaussian process regression to adapt prosthetic knee motion to varying speeds for flatground walking. Such a non-categorical strategy is more suitable for continuous and instantaneous prostheses control. A large repertoire of movements could be realized without categorical labels.

Deep learning paradigms, leveraging the availability of large datasets, are state-of-the-art at such non-categorical tasks. Processes with less clearly defined classes, such as stock-market performance and weather patterns, can be predicted by regression of their time-series data [32], [33]. We treat joint kinematic trajectories as the time series of interest and use deep learning models to continuously predict appropriate angles for the prosthetic joints, without explicitly categorizing behavior into modes.

D. OUR COORDINATED MOVEMENT (CM) CONTROLLER

We have developed a continuous controller that can generate prosthetic joint kinematic trajectories for a variety of unstructured activities. Our data-driven approach is trained on locomotion data collected from various activities to predict kinematics of a target joint omitted from the input set of joints. For example, in a trans-tibial prosthetic application, this target joint would be the ankle joint. The body motion of the person with the amputation would serve as the inputs and the predictions generated by the network could be used for the control of the prosthesis.

In [34], we demonstrated a proof of concept, generating ankle joint trajectories, but for structured rhythmic activities (flat ground walking and stair ambulation.) In [35] we expanded the envelope of operation to include non-rhythmic movements and agile maneuvers.

Our previous studies [34], [35] were limited to conceptual and offline results on previously collected data on ankle joints only. In this study, we have improved the system to include the knee and ankle simultaneously. We measure how the performance is affected by conditions such as the sensor locations and amount of data. We also demonstrate the feasibility of using this coordinated movement strategy to control a single prosthetic joint. We describe here a real-time controller to acquire live kinematics and actuate a powered knee prosthesis [1] for treadmill walking. The preliminary results of this study were included in the first author's doctoral dissertation [36]. In this peer-reviewed manuscript, we collate the key results pertaining to the application of CM control to unstructured activities. We also expand upon and report the performance of CM control around hard and atypical transitions.

The main contributions of this paper can be summarized as follows:

1) We present a system to simultaneously predict the knee and ankle joints angles based on inputs from the rest of the body, for a previously unseen subject. We investigate the offline performance of this system for rhythmic and non-rhythmic activities, including the transitions.
2) We analyze the dependence of the performance on the complexity of the movements involved in the activity, input sensor configuration, amount/variance of data.
3) We test the feasibility of real-time control of a single joint (knee) robotic prosthetic leg for a treadmill walking task. This demonstrates that data acquisition, joint angle estimation, and actuation can all be achieved within reasonable real-time speeds using standard hardware.

II. METHODS

The study consisted of 3 main experiments:

1) Collecting the data from 63 non-amputees participants performing various activities,
2) Offline Tests: Training a neural net to predict the knee and ankle movements of 3 non-amputee subjects (excluded from the training set),
3) Real-time Test: Using the trained model to control the knee joint of a powered prosthesis for 1 non-amputee participant (excluded from training and offline tests).

A. PARTICIPANTS

Ambulation data was collected for a total of 63 participants (34 male, median age 25) with no amputation or other mobility impairments. Recruitment and human subject protocols were performed in accordance with the local University of Washington Institutional Review Board approval and each subject provided informed consent. De-identified data can be made available, via a data use agreement, upon request to the authors. 11 subjects performed flat ground walking activity and 42 subjects performed stairs activity. To investigate atypical and non-rhythmic movements, 10 subjects performed 3 activities from the Comprehensive High-Level Activity Mobility Predictor (CHAMP) test (Table 1). The CHAMP test was designed as a safe performance-based measure of high-level mobility for those with lower-limb loss (See Section II-B3).

B. ACTIVITIES

The movements targeted in this study were designed to be more challenging to be categorized into modes.

TABLE 1. Distribution of subjects across the 3 different activities.

Group	*Activity*	*Number*
Group A	Flatground walking with random stops	11 subjects
Group B	CHAMP Tests	10 subjects
Group C	Stair ascent & descent	42 subjects

1) FLAT GROUND

To replicate regular community ambulation, flat ground activity consisted of walking on a long corridor in a public building. This included random stopping to incorporate transitions between steady-state walking and rest.

2) STAIRS

This activity consisted of stair ascent and descent in a 6-story public building. This included sections of flat ground transitions in between levels.

3) COMPREHENSIVE HIGH-LEVEL ACTIVITY MOBILITY PREDICTOR (CHAMP)

The CHAMP test was designed as a safe performance-based measure of high-level mobility for those with lower-limb loss (LLL). The CHAMP test consists of 5 activity sets, but here we selected a subset of 3 activities that focus on agile movement, as opposed to balance or endurance. These are the Edgren Side Step, the Illinois Agility Test, and the T-test. They include challenging abrupt changes in the movement direction, running, and backward locomotion. These standard tests are described in detail in [37], [38] and summarized below.

a: CHAMP ACTIVITY 1: EDGREN SIDE STEP

Five cones are placed in a line three feet apart. The participant, starting from the center cone, sidesteps to the right until their right foot crosses the outside cone. The participant then sidesteps to the left until their left foot crosses the left outside cone. The participant sidesteps back and forth to the outside cones for 10 seconds.

b: CHAMP ACTIVITY 2: ILLINOIS AGILITY TEST

The test aims to complete a weaving running course in the shortest possible time. The length of the course is 10 meters and the width is 5 meters and cones mark the course. On the ‘Go’ command, the subject runs the course, without knocking down any cones.

c: CHAMP ACTIVITY 3: T-TEST

A course 10 meters long and 3.5 meters wide is marked by cones in a ‘T’ shape. Successful navigation requires side shuffling to reach the left and rightmost cones as well as backward walking to return to the starting location.

C. INSTRUMENTATION

We collected locomotion data using the Xsens Awinda suit [39], consisting of 17 body-worn sensors placed at key locations, shown in Fig 1. Each sensor has a tri-axial gyroscope, accelerometer, magnetometer, and barometer. Xsens Analyse software integrates these individual sensors and renders a full-body avatar. After a system specified calibration, the software provides position and joint kinematics in a 3D environment. Although other data such as limb-segment position, orientation, acceleration are available, we used only joint angles for this study. All angles are in 1×3 Euler representation of the joint angle vector (x, y, z) in degrees, calculated using the Euler sequence ZXY using the International Society of Biomechanics standard joint angle coordinate system [40]. Data, sampled at 60 Hz, from a total of 22 joints in 3 anatomical planes (sagittal, frontal, transverse) were captured for each trial, which results in 66 total possible features for our machine learning methods.

D. DATA COLLECTION

The subject donned the Xsens suit and performed the calibration procedure. A brief test was done using the Xsens Analyze software to ensure that the quality of data being recorded was good. The subjects then performed 10-15 minute trials of the desired activity. For flat ground and stairs activity, the subjects were instructed to walk naturally at a self-selected pace. The data for these activities was collected in public spaces during active business hours, with the intent that normal gait dynamics and corrections would appear in the example data. The order of activities, starting and ending points were randomized. The experiment was completed in a single session which lasted less than 2 hours. In total, 750 minutes of data were collected from all subjects.

E. DATA PROCESSING

Sensor data was visually inspected to detect any potential equipment malfunctions or calibration problems. Sensors getting displaced from their original calibrated location is a commonly seen issue with wearable motion capture systems. If this was detected during the experiment, sensor placement was corrected followed by recalibration and reinitialization of the suit.

Xsens features a real-time engine that processes raw sensor data for each frame, algorithmically fits the human body model to estimate anthropomorphic joint and segment data. A post-processing engine includes information from the past, present, and future to get an optimal estimate of the position and orientation of each segment. This ‘HD’ processing raises the data quality by extracting more information from larger time windows and modelling for skin artifacts, etc. but also takes a significantly longer time.

We used HD processed data as training data for our neural networks. The real-time benchtop test, however, used only real-time (non-HD processed) data.

F. MACHINE LEARNING MODEL AND ARCHITECTURE

Previously [34], we investigated three different regression models: Multivariate Linear Regression, Fully-Connected

TABLE 2. Distribution of subject data for training, test and validation sets for each of the cross validation runs. This process was repeated thrice with random shuffling and the average result across the 3 runs was reported.

	Flatground	CHAMP	Stairs
Train	9 subjects Group A	8 subjects Group B	40 subjects Group C
Test	1 subject Group A	1 subject Group B	1 subject Group C
Validation	1 subject Group A	1 subject Group B	1 subject Group C

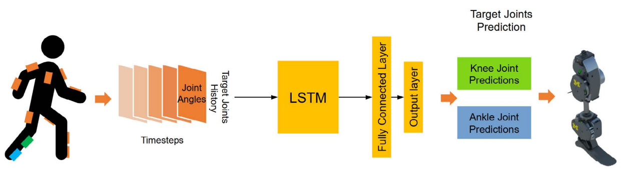

FIGURE 1. Neural Network Architecture. Each layer computes information based on the previous layer, but also using its own previous outputs and an internal memory. For offline tests, we generate predictions for both ankle and knee joints, and report the performance. For real-time tests, we use the pre-trained network to generate predictions for only the knee joint and control a prosthetic leg.

Deep Neural Network, and a variant of Recurrent Neural Network - Long Short-Term Memory (LSTM) [41]. It was shown that the Recurrent Neural Network with a short time history of gait movements provided the best prediction of the right ankle joint. In this study, we use the same network architecture, shown in Fig.1. However, we increase the number of joints predicted to two by including the knee joint as well. The deep-learning networks were implemented on PyTorch [42].

In the real-time prosthetic controller, the trained network would be applied to predict joint trajectories for a user whose movements would not have been captured in the training dataset.

For the offline tests, we used a K-fold cross-validation method to report generalized results. The subjects were randomly split into training, validation, and test with no overlapping subject data. Table 2 shows the distribution of subjects. The validation data was used to tune the hyper-parameters and the test set was used to report performance for that particular run. This process was repeated thrice with a random allotment of subjects as training, test, and validation data. For each run, 57 subjects were included in training set, 3 in test and 3 in validation set. The final results reported were averaged across the three runs. The data for the test (and validation) set was combined from 3 test subjects such that all 3 activity types were included.

Given a time series trajectory of M intact joints $x \in \Re^{M \times T-1}$, we employ the LSTM network model to estimate current target joint values $\hat{y_T}$ at time instant T.

$$\hat{y_T} = f(x) \tag{1}$$

where f is the LSTM network.

d: DATA NORMALIZATION AND RESHAPING

Each of the joint angles exhibits a different Range of Motion (ROM). To prevent high-ROM joints from dominating predictions, it is common practice to normalize all features (generally 0 to 1). We normalized all joint angles for every trial and saved the average scaling factor of the training samples for de-normalizing the predicted joint angles.

e: ROLLING TIME WINDOW

During training, LSTMs backpropagate errors a specific number of time steps back. This parameter, known as the sequence length, affects the time scale that the LSTM cell state reasons about. Choosing a longer sequence length increases the number of parameters that need to be trained, increasing computational load and requiring more training data. Choosing a shorter sequence length increases the difficulty of learning time dependencies in the data. In practice, choosing a sequence length appropriate to the inherent temporal dynamics of the problem greatly simplifies training and performance of the network [43]. Training input samples were prepared as an overlapping rolling window of time series data of desired sequence length. The optimal sequence length was a hyperparameter we tuned for.

f: LOSS FUNCTION AND NEURAL NETWORK HYPERPARAMETER OPTIMIZATION

We used the mean squared error (MSE) between the predicted and measured joint angle as loss function to be optimized. This is a common metric used for regression tasks in machine learning. Apart from the sequence length, the network also has several hyperparameters that need to be optimized for different application domains.

g: HYPERPARAMETER OPTIMIZATION

A combination of random and grid search was applied to optimize hyperparameters. Each batch was shuffled and random Gaussian noise was added to each sample to reduce over-fitting.

Optimized hyperparameters included batch size, number of epochs, number of layers (L), number of units in each layer (HU), the standard deviation of the injected noise, the regularization parameter for L2 loss (λ), and learning rate.

Every 5 epochs, the performance of the model was evaluated on a validation set. The best-performing model was saved and used to generate predictions and metrics on a test set. 30 trials were evaluated for each parameter set and the average Root Mean Squared Error (RMSE) was recorded. The optimal parameter value selection was based not just on the absolute best performance but also considering the overhead in time and computation needed to reach that performance. The range of parameter values tested is shown in Table 3. The optimal hyperparameter set was used to compare and evaluate performance.

TABLE 3. Hyperparameter values tested for optimal performance on Obstacle course data-set.

Hyperparameter	Range/Values	Optimal
Learning Rate	$[10^{-5} : 10^{-2}]$	10^{-3}
Batch Size	[1000,10000,50000,100000]	50000
Number of Epochs	[200,500,750,1000]	500
Input Sequence Length	[1,2,5,10,15,20,25,30]	10
Number of LSTM Layers	[2,4,8,12]	2
Number of Hidden Units	[4,8,16,32,64,128,256]	64
Regularization Rate	[0,0.05]	0
Random Noise (std)	[0.01 : 1]	0.02

h: DENORMALIZATION

To report results in the original scale, all predictions were denormalized using average minimum and maximum scaling factors extracted from the training set only. This is common practice in machine learning as the test set scaling factors are not known a priori.

G. ANALYSIS

We use Root Mean Squared Error (RMSE) and the Pearson correlation coefficient (PCC) as our outcome measures to report performance for different activities, sensor groups, and quantity of data. Ideally, the RMSE will be equal to zero degrees and PCC would be equal to 1.

1) PERFORMANCE BY ACTIVITY

We compared the performance of sagittal plane ankle and knee joint angle predictions for models trained on data from:

- Flat ground walking with random stops
- Stair ascent and descent with flat ground sections
- CHAMP tests

We combine all the activities in training and report errors for each activity evaluated separately. This prevents averaging out of errors across activities.

2) DEPENDENCE ON SENSOR CONFIGURATION

We assessed performance for flat ground, stairs, and CHAMP activities for the following sensor groups as inputs:

- Full body (20 joints) in all 3 anatomical planes
- Lower limb (6 joints) in all 3 anatomical planes

3) DEPENDENCE ON DATA

We assessed performance for different amounts of training data by varying:

- Number of subjects included in training data.
- Percentage of data included from *every* subject in training data.

a: SIGNIFICANCE AND EQUIVALENCE TESTING

R-package and Matlab were used for statistical analysis. Simple rhythmic movements of flatground walking should be easier to generalize than those involved in the CHAMP tests. Hence, we expected the performance to vary with activity. Similarly, more training examples collected from more subjects should allow the network to learn more variations and hence perform better. For these outcomes, we use paired-sample t-tests. Effect sizes were calculated using cohen's d method [44].

In contrast, we expected most of the movement cues for flatground walking to be present in the lower body. We also expect a diminishing return by adding more training examples from the same subject as they would likely be similar. Hence, we hypothesize that sensor configuration and percentage of data from every subject will not result in significant differences in performance. For these outcomes, we perform equivalence testing. A relevant bound around the mean value is needed within which the results can be considered "equivalent". We apply the "two one-sided t-tests" (TOST procedure) [45], one for the lower bound and one for the upper bound, to show that the change is statistically equivalent to zero.

Upper and lower bounds of 3 degrees was used for the flat ground activity. This value corresponds to the best case minimum detectable change (MDC) for sagittal plane ankle joint kinematics in literature [46], [47]. MDC for other activities has not been established. We discuss the motivation and implication of using this value in the discussion section.

H. REAL-TIME EXPERIMENTS ON THE OPEN SOURCE LEG

The Coordinated Movement (CM) controller 1) acquires kinematics 2) pre-processes the data (See Section II-F a,b), 3) predicts the prosthetic joint trajectories, and 4) translates these predictions into lower-level controls. We performed a proof of concept experiment using a real-time powered prosthesis to demonstrate acceptable latency and performance.

We used the Open Source Leg (OSL) [1], a modular lightweight robotic leg designed to be a common hardware testbed for prosthetic control research. It provides an open-source API to control the position, torque, and impedance of the knee and ankle joint, making it an ideal platform to compare different control strategies.

A person with no amputation wore the Xsens motion capture suit and a bypass socket to attach the OSL while ambulating on a treadmill at a self-selected speed (Fig 2).

A real-time controller built using Xsens Python SDK acquired live kinematics as inputs. Right ankle and knee joints were omitted as they were the intended target prosthetic joints. An LSTM neural network (see Section II-F) pre-trained on offline flat-ground walking data (to match the treadmill walking) was used to predict right ankle and knee joint kinematics from the inputs. These predicted joint kinematics were encoded to actuator positions on the Open Source Leg. Although the controller predicts both knee and ankle joint trajectories, for the sake of simplicity and safety, only the knee joint was actively controlled. A passive ankle prosthetic was mounted on the bypass socket. The controller ran on a GPU-powered laptop tethered to the OSL. The participant was asked to walk at self-selected speed on the treadmill.

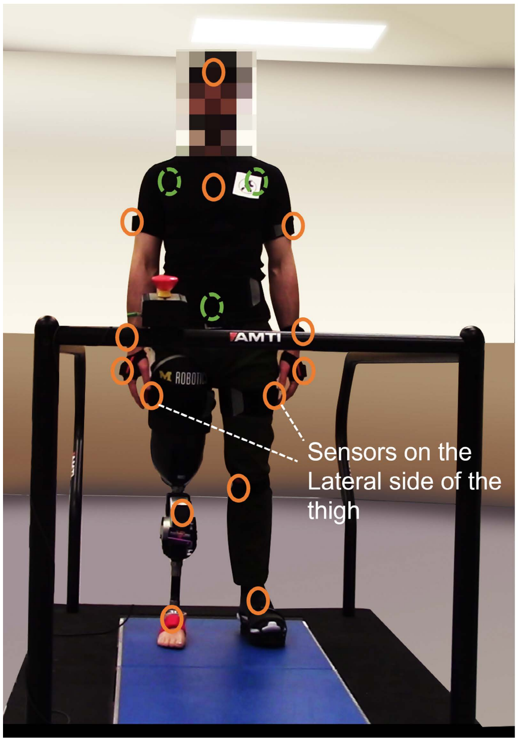

FIGURE 2. Real-time setup with Open Source Leg (OSL). The positions of imus are indicated using circles. Green dashed circles mean that sensors are placed on the posterior side of the body and are not shown in the figure.An individual wearing the motion capture sensors walked on the treadmill at a self-selected speed. Live kinematics from the suit were used as inputs to a pre-trained network that generated right ankle and knee predictions. These predictions were used to actuate the knee joint of the OSL in real-time. The ankle was locked.

The right leg sensors of the Xsens system were placed on the prosthesis (instead of the biological limb in the bypass socket) to comply with the human subject model of the system as well as to acquire the current prosthetic knee angle.

III. RESULTS

The coordinated movement controller generated continuous real-time trajectory predictions for all the activities as shown in Fig. 3. Whole-body kinematics of 19 joints in 3 anatomical planes were inputs to predict the instantaneous position of the right ankle and knee joint. Fig 5 shows an example of a smooth transition from stair descent to flatground. A complete rotation executed during the Illinois Agility Test (IAT) and transition from side-stepping to backward walking executed during T-test activity is shown in Fig. 6. All transitions were predicted successfully and instantaneously, however, performance varied across different types of activities. While the more structured activity of stair descent had an RMS error of 2.68 degrees, the CHAMP transitions showed a marked increase in the error of 5.9 and 7.6 degrees respectively.

A. PERFORMANCE WITH RESPECT TO ACTIVITIES

Ankle and knee joint prediction performance varied with activity (Fig. 4) but were within 7.5 degrees RMS error and generally showed a high Pearson Correlation Coefficient (PCC) > 0.85 (Table 4).

TABLE 4. Pearson correlation coefficients of predictions with respect to activities. Mean and standard deviations shown for ankle and knee joint sagittal plane predictions. Correlation dropped significantly for both joint predictions with increasing complexity of the activity.

	Ankle		Knee	
	mean	std	mean	std
Flat-ground	0.91	0.024	0.97	0.0067
Stairs	0.86	0.070	0.96	0.0015
CHAMP	0.72	0.066	0.88	0.026

TABLE 5. RMS errors of predictions as percentages of range of motion. The CHAMP activity had the highest error percent for both joints.

	Ankle			Knee		
	Error (degs)	ROM (degs)	Error (%)	Error (degs)	ROM (degs)	Error (%)
Flat ground	5.6	50.3	11.2	3.6	77.15	4.7
Stairs	4.7	78.2	6.0	4.4	99.59	4.4
CHAMP	7.5	46.4	16.3	6.7	70.34	9.5

The CHAMP activity predictions had reduced performance for both joints, suggesting that the complexity of movements involved in an activity impacts prediction performance. PCC reflected a sharper contrast (Effect Size = 7.9) but RMS error showed a similar trend (Effect Size = 4.3). The RMS error of predictions was generally within 12% of the range of motion for each activity (Table 5). The only exception was the ankle joint predictions for CHAMP activities with about 16.3%. Similarly, the ankle joint predictions for CHAMP activities (Table 4) had the lowest correlation of 0.72. Predictions for stairs activity with training data from 40 subjects had approximately the same performance as the flat ground activity with 10 subjects. Training data from more subjects could have a similar benefit to performance for CHAMP activity as we discuss in the following section.

B. DEPENDENCE ON SENSOR CONFIGURATION

All activities showed approximately the same performance (<0.5-degree change) when only the lower-limb sensor data was used as inputs. (Fig 7). Significant equivalence was determined for flat-ground activity using the TOST procedure as described in Section II G. Equivalent performance with a reduced set of sensors has beneficial implications for deployment with minimum instrumentation. The performance showed slight but statistically significant degradation in the case of more complex activities like stairs and CHAMP. We expect a larger sample size of participants and movement repertoire to elucidate the impact of sensor placement on various activities.

C. DEPENDENCE ON DATA

Fig. 8 shows performance with varying amount of stair activity data. Prediction RMS error significantly decreased ($p<0.001$) with data from more subjects included in

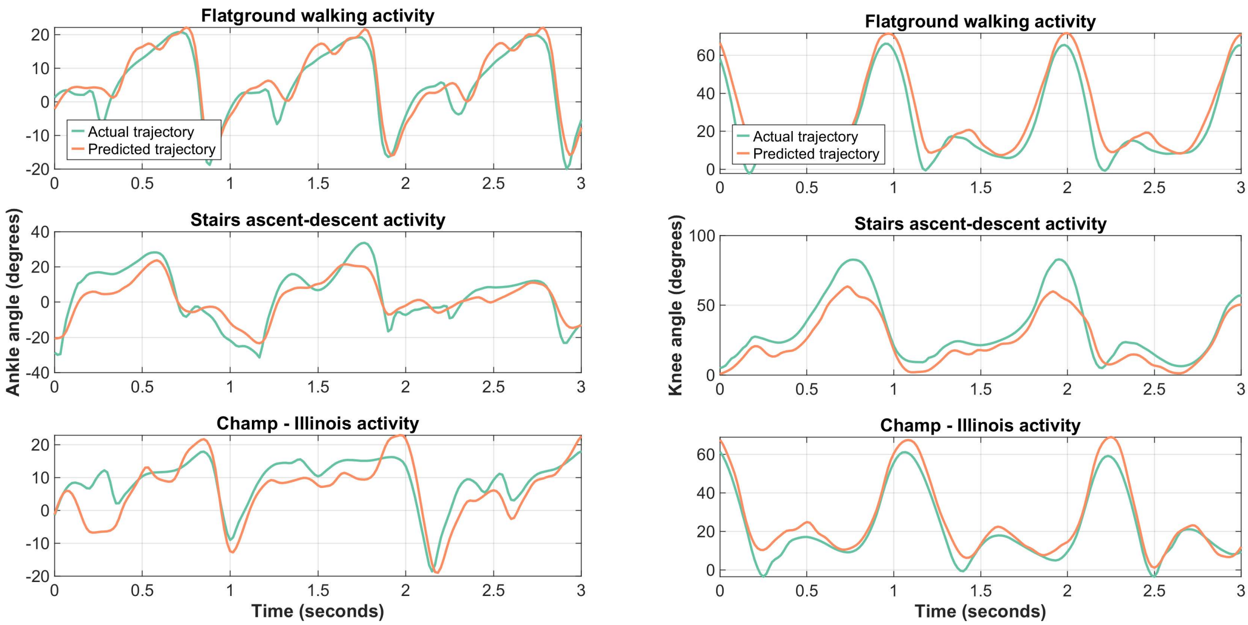

FIGURE 3. Ankle (left) and knee (right) joint predictions for 3 different activities generated by the same network.The trajectories shown for a test subject whose data was not part of the training data. About 3 seconds of actual measured (green) and predicted (red) trajectory for flat-ground (top), stair ascent-descent (middle), and Illinois Agility Test (bottom) activities are shown. Though these activities are presented separately, the network that generated these predictions was trained on a combination of all of them and did not require activity categorization.

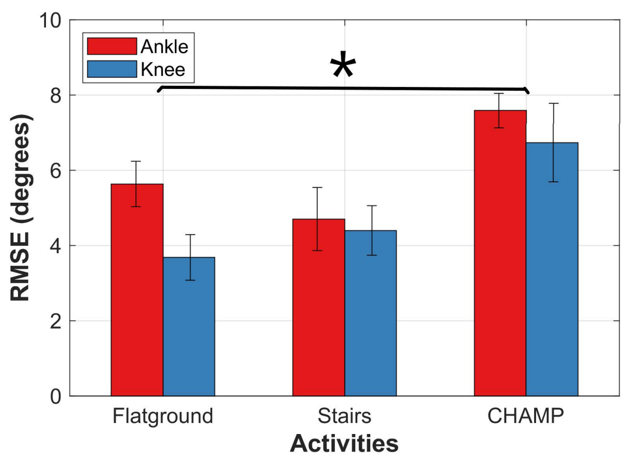

FIGURE 4. RMS error with respect to individual activities for ankle joint (red) and knee joint (blue) sagittal plane predictions. Performance was within 8 degrees RMS error for all activities and both joints. Statistical analysis showed that complexity of activity significantly increased RMS Error.

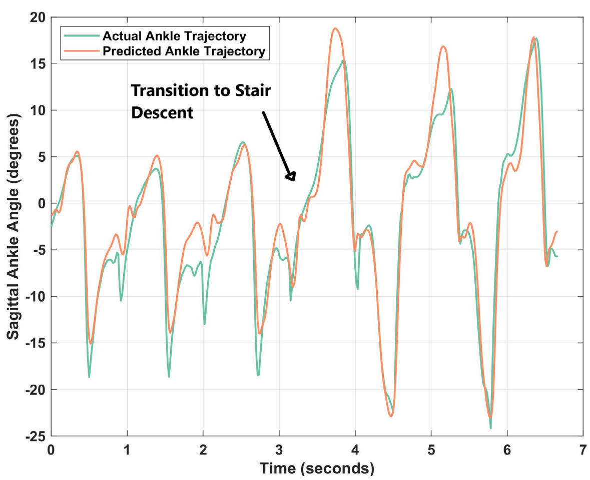

FIGURE 5. Ankle joint predictions showing continuous seamless transition from flat ground walking to stair descent.

training the models (blue). This is an important result suggesting that the performance of hard activities can be improved with training data from more subjects. Interestingly, the error remained approximately the same even when half the data from all subjects was not included in the training (orange). This could be because adding more data from the same subject does not add any new variation to the overall repertoire of movements seen by the network.

D. REAL-TIME TEST

A single individual who was not a part of the training cohort was used for a systems test. Kinematics were collected as they walked on a treadmill at a self-selected pace. These data were played as inputs to predict ankle and knee joint trajectories for the Coordinated Movement controller for a prosthetic limb in real-time (Fig. 9). The actuated trajectory had an RMS error of 8.1 degrees with respect to the network predicted trajectory. Visual analysis shows that the predictions were noisier than the offline results seen in Fig. 4 for flat ground activity due to reduced quality of input kinematics in the

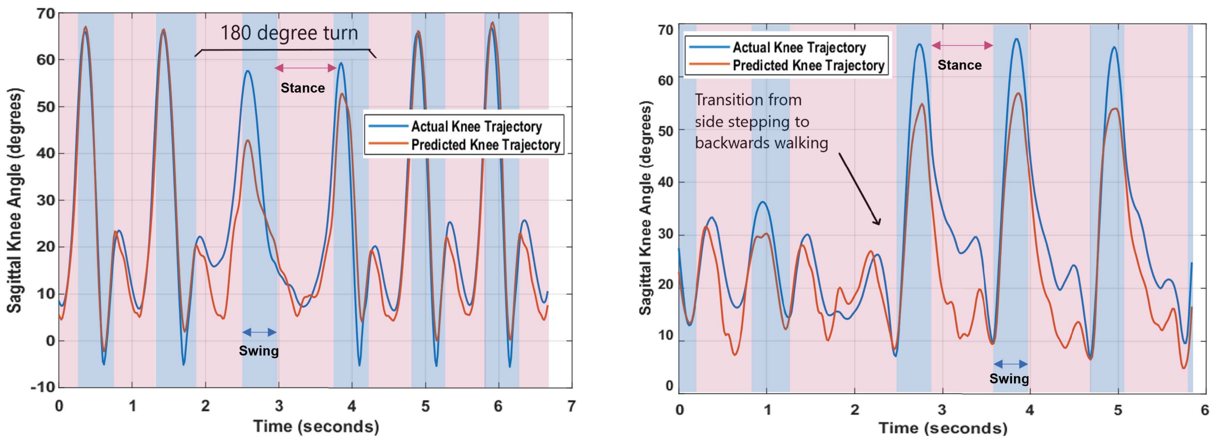

FIGURE 6. Knee joint predictions showing continuous seamless transitions in 180-degree rotation executed during the Illinois Agility Test (left) and from side-stepping movement to backwards walking in T-test (right). Swing (blue) and stance (pink) phase depicted with background color.

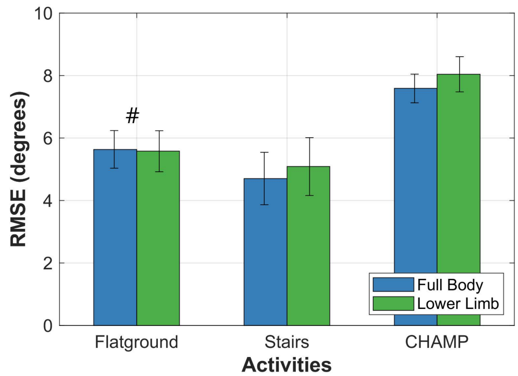

FIGURE 7. RMS error for ankle joint predictions with respect to activities with fullbody (blue) and lower limb only(green) sensors as network inputs. Using only the lower limb sensors for training showed equivalent performance for flat ground activity and a slightly worse performance in the case of more complex activities. # indicates statistical equivalence.

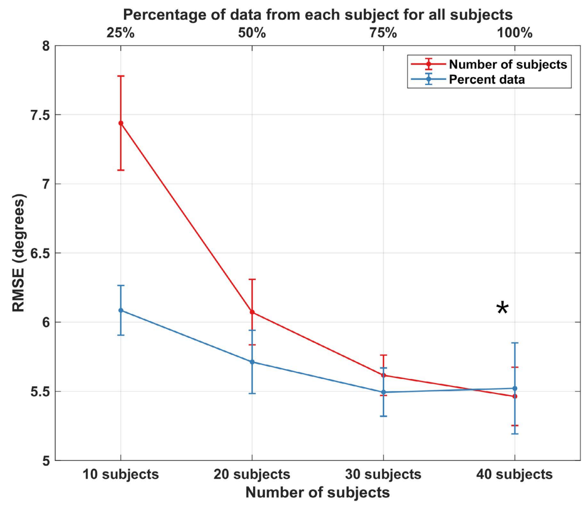

FIGURE 8. RMS error with respect to the number of subjects (red, bottom X-axis) and percentage of data used from all subjects (blue, top X-axis) for stair ascent and descent data. More subjects included in training data resulted in a statistically significant performance gain. Keeping the total number of subjects the same (n=40), but using only 50% of the data showed approximately the same performance.

real-time scenario. The whole pipeline was operated at 60Hz and the system noted a low latency (<80ms) in generating and executing these trajectories.

IV. DISCUSSION

This study aims to address the challenges faced by powered lower limb users during unstructured activities such as side shuffling and weaving around obstacles. We demonstrate here that a data-driven approach could be applicable to realize continuous control of multi-joint powered prostheses without explicit categorization of movements.

A. AUGMENTING CONTINUOUS CONTROL

Coordinated Movement control offers a way to expand the repertoire of prosthetic movements without tuning activity, specific controllers. This shifts the burden of design from tuning controller parameters to collecting examples of representative movements and training predictive neural networks.

In [3], a single-phase variable mapped to prosthesis joints allowed the execution of atypical movements like backward walking, kicking a football, etc. The phase variable, also the control input, restricted to the prosthetic side thigh angle eases instrumentation needs. However, the thigh angle is not a monotonic signal throughout the stride with discontinuities at the beginning or end. Using thigh angle and footswitches to differentiate stance and swing phases, the authors noted jumps and oscillations during transitions [13]. To circumvent this, the gait cycle was divided into different sections corresponding to different states of a Finite State Machine, and a piecewise control was implemented across the complete cycle [3]. The states of the FSM corresponded to monotonic thigh angle trajectory and provided continuity and directionality along the stride. However, it comes at

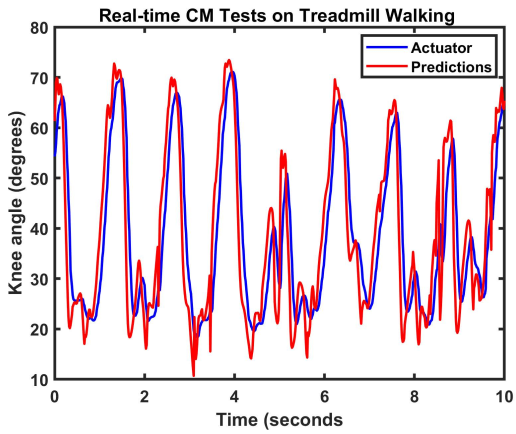

FIGURE 9. Knee joint predicted (red) and actuated trajectories (blue) during the real-time tests with treadmill walking activity. For this trial, the actuated trajectory had an RMS error of 8.1 degrees with respect to the network predicted trajectory (red).

the expense of more control states with hard-coded state transition rules and parameters. Moreover, since the FSM states were parameterized based on normative flatground walking trajectory, the non-rhythmic movements possible were encompassed within that repertoire. Adding other non-rhythmic movements to the fold, or even rhythmic activities such as stair ascent would require a different FSM with state transition rules pertaining to the corresponding kinematic trajectories.

CM can be thought of as a more expressive continuous controller. Despite the added instrumentation, the inclusion of more of the body allows for a variety of possible whole-body movements. We show here the sensor configuration can be limited to the lower body without a significant loss in performance for simple activities. The likelihood of having different output prosthetic joint positions for a given control input is also lower and avoids jumps and oscillations within a stride. The addition of time-history of joint poses as the inputs, as opposed to just a single time instant, also benefits the number of possible output configurations, needed for a wider range of movements. However, this expressiveness could also be harder for the user to predict.

Direct continuous EMG control has also garnered interest to mimic the biological neural control paradigm. Using continuous muscle signals to modulate prosthesis dynamics, this strategy can theoretically be applied to achieve control for unstructured and non-rhythmic activities. Potential benefits include restored reflexive muscle activity and improved prosthesis embodiment [25]. However, practically mapping of multiple muscle activity to joint dynamics, especially position, is an extremely complex many-to-many relationship and is a topic of research. Several methods like principal component analysis, non-negative matrix factorization, musculoskeletal models have shown success [22], [26]. Current evidence is mostly limited to target reaching tasks [21], [22] or well-defined movements such treadmill walking, postural control, sitting, stair climb [23]–[27]. Achieving desired control requires training, aid of visual feedback [21], [22], [24] and is associated with overall increased mental load [27]. We expect direct EMG to benefit from the intelligence and movement repertoire afforded by CM control; much like NMI [4], where combining EMG and mechanical sensors improved overall locomotion mode classification accuracy. CM strategy's ability to determine the desired unstructured movement using natural body movements could be augmented by direct EMG to modulate the torque and effort within the movement.

B. A UNIFIED CONTROLLER FOR VARIED ACTIVITIES

Our CM controller was trained on data from different activities and can generate movement for any of them, as well as the transitions between them, seamlessly. For example, Fig. 5 shows an example of ankle angle as a user transitioned from walking on flat ground to descending stairs. Even harder changes in movements such as turning around involving rapid changes from and back to the flat ground straight walking, as well as transitions to backwards walking were predicted by the same network (Fig 6). However, the error was increased for these harder movement transitions.

Although a single CM controller can generate predictions for all activities included in the training data, the performance for each activity varied. The CHAMP activity predictions (Fig.4) showed significantly higher RMS error than flat ground activity. This could be due to the complex collective of movements that included weaving around obstacles, walking sideways and backward. This suggests that complexity of activity impacts performance and it seems likely that more training data could benefit such activities, as we discuss below.

C. SENSOR CONFIGURATION

An interesting result is that using only lower limb sensors had approximately the same performance as using full-body sensors (Fig.7). This suggests that, in the interest of minimum instrumentation and cost, this system could be deployed with just lower-limb sensors without compromising overall performance.

We expected the CHAMP activity to benefit from the inclusion of the upper body sensors given the relatively complex movements involved. Evidently, most of the information for the activities in this study was captured by the lower limb data. However, this result should be considered with a caveat. Upper limb movements are integral to maintain dynamic stability and perhaps more intricate activities that demand whole-body coordination would benefit from full-body data.

D. PERFORMANCE DEPENDENCE ON DATA

The performance was significantly improved when more subjects were included in the training data. This peak performance was maintained even when half the data from *every* subject was excluded from training (Fig. 8).

These results have two implications for more efficient data collection protocols in the future. Firstly, as expected, a data-driven approach relies on, and benefits by including data from more subjects. Secondly, less data from more subjects is better than more data from fewer subjects.

With an equal number of subjects (n=10), the RMS error of predictions for stair activity was significantly greater error than flat ground activity. The inclusion of 30 more subjects (n=40) reduced this error by almost 2 degrees, bringing it closer to flat ground prediction performance. This suggests that relatively more training data are needed for more complex activities to achieve a performance similar to simple rhythmic activities. We expect the result to hold for CHAMP activity, including the transition sections, as well.

E. CONTROLLING KNEE AND ANKLE SIMULTANEOUSLY

All control methods require tuning of parameters, but the burden of this generally depends on how many parameters need to be tuned. Recent work has pointed out this problem [14] and methods for automatic tuning are being investigated [15], [16]. Controlling multiple degrees of freedom, such as both ankle and knee, or additional planes of motion, can greatly increase the number of required parameters to be tuned. If the controller is specific to a locomotion mode, then adding additional modes requires additional tuning as well. The coordinated movement regression approach that we describe here is comparatively insensitive to additional degrees of freedom. The process remains the same: collect examples of desirable movement profiles, and perform regression on the desired degrees of freedom to be controlled. We suggest (though this study does not explicitly demonstrate) that this approach could produce more complex control outputs with a comparatively less tuning burden.

Predicting both knee and ankle is more difficult than predicting only the ankle for two reasons. The first is simply that the network has two outputs to learn. The second is that the knee joint input data itself is highly salient for predicting the ankle joint. In our previous work [34], [35], we predicted only the ankle joint. The error we observe in the present study is higher, but only noticeably so in the CHAMP activity (Fig. 10) with a 21% increase. We speculate that simpler movements contain more redundant information in the remaining joints. For more complex activities like CHAMP, the value of the ipsilateral knee joint is higher.

The difficulty of controlling multi-joint robotic limb was highlighted during the real-time test. As we discuss below in-depth, the predicted trajectory during the real-time test was noisier than offline results. The disturbance observed by the user was compounded and more pronounced with both ankle and knee joints of the OSL being actively controlled. To simplify the test procedure and also to ensure participant safety, only the knee joint of the OSL was actively controlled by the network predictions. A passive ankle was attached to the distal end of the bypass socket.

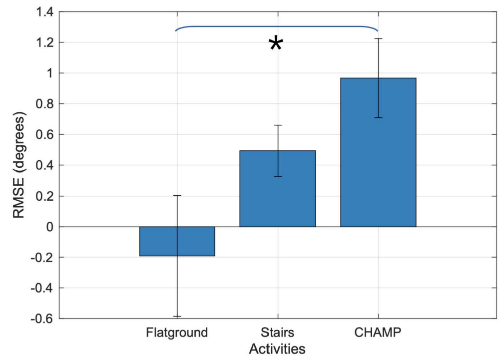

FIGURE 10. Change in degree RMS error for ankle joint predictions without the ipsilateral knee as one of the input joints. Cyclic activities like flat ground walking offer more redundancy in other joints whereas unique activities require more input joints for prediction. A relatively complex CHAMP activity showed a 1 degree or 21% increase in error comparing the ankle only results in our previous study and the knee and ankle results of this study. Asterisk indicates statistical significance.

F. REAL-TIME TEST

The real-time test was designed to test the feasibility of a data-driven controller to actuate a prosthetic leg. The system showed low latency in predicting and generating the reference trajectories. The whole pipeline of operations resulted in a lag of less than 80ms in the response of the prosthetic leg. For upper-limb prostheses, a delay greater than 300ms is considered significant [48]. This value has not been established for lower-limb prostheses, but it can be generally deduced that lower delays are desirable, especially during load bearing phases. Despite switching to the passive ankle, estimates were still generated in real-time for both knee and ankle, to demonstrate the computational feasibility and latency. We expect the minimum inherent lag of this strategy to be lower than 80ms when optimized for a production-level implementation. Although training this kind of model can be quite computationally expensive, runtime implementations can be made to be significantly faster than what we report here.

In offline tests, normative biological limb trajectory was used as ground truth to quantify prediction errors. For a real-time test, however, there is no such thing as a ground truth trajectory; the user moves in concert with the prosthesis, reacting to it as a coupled system. Fig. 9 depicts a representative 10-second window from the experiment. The predicted knee trajectory (red) appears appropriate, and the device can approximately track it (blue). However, we observed that the predicted trajectories were noisier than in offline experiments, characterized by greater variance and undesirable features such as the back-and-forth spikes at the extrema. These disturbances were more perceptible with both ankle and knee joints of the OSL being actively controlled, and sometimes compromised the stability of the participant. Substituting the active ankle joint with a passive ankle allowed the participant to walk more easily, albeit with occasional kickbacks. Smoother position-based command trajectories could be obtained, if desired, to improve comfort or confidence in the system. On the other hand, a system commanded by impedance-based trajectories may be more forgiving of such inherent noise of the predictions.

We suspect that the noisier outputs could be due to noisier inputs from the motion capture system. Raw motion-tracking data is inherently noisy. The Xsens real-time engine mitigates this by accommodating sensor drifts and correlating independent sensor data to a human body model. A post-processing engine further improves data quality by including past, present, and future samples. While offline analysis has the benefit of using clean post-processed data, real-time control does not. This results in poorer prediction performance. This deviation in the distribution of the data in the test compared to training, known as covariate shift, is commonly seen in machine learning. This could be alleviated by using raw unprocessed data, or processed data with artificial noise, as training inputs to simulate the real-time data. Generation of synthetic training data using Generative Adversarial Networks (GAN) could allow the network to be more robust to sensor noise [49]. A more thorough long-term solution could be to engineer an algorithmically light version of the post-processing engine to operate on real-time data as well.

1) LIMITATIONS

a: ERROR METRIC

Our objective was to replicate normative joint trajectories for every instant in time. We chose our outcome measure to be the RMS error, commonly used for regression tasks. This makes it difficult to objectively compare with mode-based strategies which report accuracy in the percentage of accurate mode classification. However, the RMS metric has been used in continuous direct myoelectric control studies to report performance. For the case of flatground walking, we see [23] and [22] report an RMS error of around 6 degrees and 7.5 degrees in the sagittal plane for ankle joint kinematics. In comparison, we report an error of 5.6 degrees for the same.

Jahanandish *et al.* applied Gaussian Process Regression on spatio-temporal ultrasound features from leg muscles to evaluate continuous task-invariant learning of knee joint kinematics [50]. They report a RMS error of 4.7 and 10.7 degrees for flatground walking and stair ascent activity respectively. In comparison, we observe an RMS error of 3.6 and 4.4 degrees for the same. It is however unclear if the degree error reported in all the studies is within an acceptable threshold for *practical* use. For the case of flat ground walking, the RMS error is comparable to the Minimal Detectable Change (MDC) values of around 3 and 5 degrees [46], [47] for ankle and knee joints in the sagittal plane.

For the lack of a better measure, we use an MDC of 3 degrees to determine equivalence in the case of flat-ground activity. A similar approach has been used in other studies [51] but to show a statistical difference due to intervention. Even though the 3 degree bound was the lowest value seen in literature, it would still be large enough to show statistical equivalence for all the activities in this study. However, statistical equivalence should not be confounded with practical equivalence. These MDC values correspond to gait measurement, and may not equate to MDC for a load-bearing prosthetic application. MDC for other activities and more importantly minimal clinically important difference (MCID) for gait and prosthetic control is critically lacking [52].

Another metric used to report fidelity of the trajectories is the Pearson Correlation Coefficient (PCC). [3] reported 0.80 to 0.95 correlation for knee trajectories for flatground walking at various speeds. The PCC we observe for knee joint for flatground activity is 0.97. Once again, PCC for other more complex activities is lacking in the literature.

Regardless of the control strategy, objective metrics like, PCC, classification accuracy, and RMSE are poor windows into the more important subjective experience of the user. In [53], Zhang *et al.* investigated the effects of various kinds of errors in locomotion mode classification on user perception of instability. The study evidenced that the timing with respect to the gait phase of the control disturbances caused due to errors is an important factor. So another way to look at error could be to look at the maximum stance-phase error. For example, for flat-ground walking, the average RMSE for ankle and knee were 5.6 and 3.6 degrees, and the average max error during the stance phase was 6.77 and 8.99 degrees. Albeit higher in value, this has similar strengths and weaknesses as RMS. A study similar to [53], tying the objective metric of RMS to the subjective experience of the user, could lend insight for better comparison.

b: USE OF NORMATIVE TRAJECTORIES

We show that deep networks can represent and adapt to users *not* directly measured during training. So even though the prosthetic user's own gait may not have been recorded prior to amputation, this approach could still be employed. However, a major assumption with this approach is that normative trajectories collected from unimpaired subjects can be replayed for prosthesis users. Normative trajectories have been successfully used for prosthetic control [3], [18] and as tuning objective to optimize powered limb impedance parameters [15]. We expect a similar performance with our controller.

However, as prior studies have concluded, a more complex reference objective that accounts for variations of weight and dexterity of prosthetic limbs could be necessary. Since the dynamics of the prosthesis are different from those of the physiological leg, it could make sense to generate controls that take that into account.

c: POSITION CONTROL

The tuning of the lower-level controller gains (PID) will most likely be needed to ensure safe and comfortable ambulation. An impedance or torque-based prosthetic controller is likely to be more comfortable. Current commercial wearable sensors provide only position estimates, limiting the target predictions in this study to joint kinematics only. However, there is an increased interest in estimating joint kinetics using wearable sensors [54], [55]. Upon availability of such reference data for training, this data-driven methodology can be used to generate joint torque predictions as well.

Using only a single test participant in understanding the real-time performance of this strategy is a limitation.This is a first-step feasibility demonstration, but not yet a robust examination of controller performance. Moreover, although the controller predicts both knee and ankle joint trajectories, for the sake of simplicity and safety, only the knee joint was actively controlled.

2) IMPROVEMENTS AND FUTURE WORK

In a follow-up study to improve CM controller performance, [56], the application of Attention [57] technique to neural network drastically reduced RMS errors to less than one degree. However, real-time results on actual hardware will be evaluated as future work. Wen *et al.* [15] explored the application of reinforcement learning to automatically tune prosthetic controller parameters for flatground walking. Collaterally, the adaptive tuner reduced the average RMS error of the robotic knee angle from 5.83 degrees to 3.99 degrees. A similar approach could potentially adopt CM-generated reference trajectories to individual preference, improving performance.

Experiments in preparation are geared towards assessing the performance of this control strategy on human subjects as well as to compare it to other mode-based control strategies.

Non-time varying and subject specific features contain rich contextual information and have shown to improve network accuracy in bio-medical applications [58]. Including non temporal subject-specific data that affect gait kinematics, such as gender [59], body dimensions [60], age [61] etc. could possibly improve performance.

V. CONCLUSION

Sixty-three subjects wore a motion capture suit and performed various rhythmic and non-rhythmic activities. A recurrent neural network was trained to predict ankle and knee kinematics using the remaining joint kinematics as inputs. Performance was within 7.5 degrees RMS error for test subjects excluded from training examples. These errors are generally less than 12 % of the ROM of the corresponding activities.

A systems study was conducted, demonstrating that the data-driven predictions and controller can be run in real-time on real hardware with low latency. Further work is necessary to understand how useful this control strategy is for more realistic ambulation.

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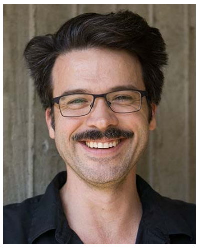

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