Transfer Learning for Walking Speed Estimation Across Novel Prosthetic Devices and Populations

Jairo Maldonado-Contreras, Cole Johnson, Ian J. Knight, Aarnav Sawant, Sixu Zhou, Hanjun Kim, Kinsey R. Herrin, and Aaron J. Young, *Senior Member, IEEE*

Abstract— **Accurate walking speed estimation in lower-limb prostheses is crucial for delivering biomechanically appropriate assistance across varying speeds. However, training robust models requires extensive domain-specific, user-dependent (DEP) data, which is impractical for every new prosthesis user. This study presents a transfer learning framework to simplify and enhance the training process. Convolutional neural networks were pre-trained on publicly available datasets from able-bodied (AB) individuals and transfemoral amputees using the Open Source Leg (OSL) knee-ankle prosthesis, then fine-tuned with data from a transfemoral amputee using the Power Knee (PK) prosthesis. The fine-tuned models, AB-PK and OSL-PK were trained with varying data amounts and evaluated across constant and variable walking speed trials, with performance compared to DEP models trained from scratch on PK data. Training and testing were conducted on a per-subject basis, with performance averaged across subjects (N=7). The lowest post-fine-tuning error was observed in AB-PK, with RMSE values of 0.041 m/s for constant speeds, 0.072 m/s for variable speeds, and 0.088 m/s for novel speeds not included in the original training data. Significant error reductions were observed in both fine-tuned models compared to DEP when fewer than 30 gait cycles per speed of training data were available. Notably, AB datasets appeared highly viable for this application and may even outperform OSL datasets in transfer learning for walking speed estimation, perhaps due to the much larger original training dataset. This approach highlights the potential of transfer learning across different subject populations and devices, offering insights into the data needed to achieve state-of-the-art speed estimation.**

I. Introduction

Powered lower-limb prosthetic devices [1], [2], [3], [4] use actuators, sensors, and microprocessors to enhance mobility for amputees by delivering net positive work, minimizing compensatory movements, and promoting a more natural gait, improved stability, and reduced energy expenditure [5], [6], [7], [8], [9], [10]. A critical component of these devices is the controller, which ensures safe and effective interactions between the user, prosthesis, and environment. Central to this control is context estimation, such as speed estimation, which drives speed-specific assistance, enabling a smooth gait across varying walking speeds. Speed-adaptive control systems for these prostheses often follow a hierarchical structure, starting with high-level controllers that estimate the user's state or environment (e.g., speed) [11], [12], [13]. This information is passed to mid-level controllers, where impedance control parameters are adjusted to modulate knee and ankle behavior [14], [15]. These parameters, whether state-specific or modeled, aim to replicate able-bodied kinematics and kinetics and adapt to different walking speeds [16]. Some systems employ a continuous strategy, using a pre-trained gait model to adjust impedance parameters based on the computed phase variable and walking speed [15].

To compute walking speed in real-time, machine learning methods have been proposed that use regression models trained on user-dependent (DEP) data [17]. Machine learning methods can match the performance of traditional walking estimation methods like direct integration [18] and kinematic modeling [19], [20]. The lowest errors achieved in amputee populations were 0.014 and 0.09 m/s RMSE for machine learning [17] and non-machine learning [20] approaches, respectively. A drawback of the machine learning DEP approach is the large up-front cost of DEP data collection, as each new user typically undergoes hours of treadmill trials at different speeds. This process can be particularly taxing for individuals with lower-limb amputations who experience asymmetric and inefficient gait, which is exacerbated across different walking speeds [21], [22]. Fortunately, open-source, multi-subject datasets [16], [23] can be used to train user-independent (IND) models that generalize well to new users. However, IND models yield higher errors [17] and often fail when applied across different user populations and devices due to variations in signal shape and quality. Given the scarcity of prosthesis-related datasets and the increasing number of custom research prostheses, there is clear value for transfer learning methods that transfer walking speed estimation knowledge between populations and devices, especially for cases with limited data.

Transfer learning is widely employed to enhance the efficiency and adaptability of robotic systems by leveraging knowledge from previously learned tasks to solve new, but related tasks. This approach is essential in robotics, where retraining models from scratch for each new scenario is often impractical. In domain adaptation, the goal is to adjust models trained in one domain (source) to perform effectively in a different but related domain (target). This is typically

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*J. Y. Maldonado-Contreras and A. J. Young were with the Mechanical Engineering Department, Georgia Institute of Technology, Atlanta, GA 30332 USA and with the Institute of Robotics and Intelligent Machines, Georgia Institute of Technology, Atlanta, GA 30332 USA (e-mail: jairoymc@gatech.edu).

C. J. Johnson and I. Knight were with the School of Computer Science, Georgia Institute of Technology, Atlanta, GA 30332 USA.

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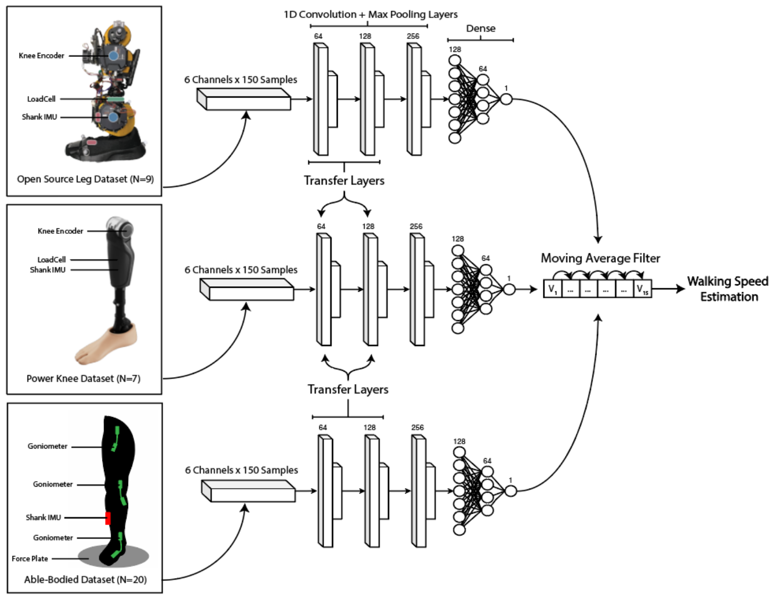

Fig. 1. This diagram illustrates the use of transfer learning in estimating walking speed. A model is pre-trained on data from two large datasets: the Able-Bodied Dataset and the Open-Source Leg Dataset. The model is then fine-tuned using a smaller, subject-specific dataset (Power Knee Dataset) from a transfemoral amputee. This approach enhances estimation accuracy while reducing the need for extensive data collection from the new subject.

achieved by aligning the feature spaces of the source and target domains, reducing domain shift. Techniques such as adversarial domain adaptation, where models are trained to learn domain-invariant features [24], are commonly applied. Another common approach is model-based transfer learning, in which an entire model or parts of a model trained on the source task are transferred to the target task. Typically, the pre-trained weights from a neural network trained on the source task serve as the initial parameters for training on the target task. This is followed by fine-tuning to adapt the model to the specific requirements of the target domain [24]. These techniques are particularly useful in scenarios where labeled data in the target domain is scarce, making transfer learning a powerful tool for tasks involving robotic systems and prostheses.

Employing transfer learning enables the creation of foundational models from large datasets that can generalize across different populations and devices, ushering in a new paradigm in prosthetic device development where high-quality data collection becomes crucial. This approach also enhances accessibility and lowers the barriers to entry for developing new powered prosthetics, allowing for more personalized and effective solutions in the field. Transfer learning has already demonstrated strong results in the control systems of hand prostheses, such as in transferring sEMG decoders between subjects [25], improving EMG pattern recognition systems [26], and in ambulation mode classification for lower-limb prostheses [27], [28].

In this study, we employ a domain adaptation and Convolutional Neural Network (CNN) model-based transfer approach to fine-tune speed estimation models for a novel device with limited user- and device-specific data. We pre-train two separate CNN models: one on data from transfemoral amputees using the Open Source Leg (OSL) knee-ankle prosthesis, and another on data from able-bodied (AB) individuals, allowing for a comparison of their performance. Models are then fine-tuned using varying amounts of data from transfemoral amputees using the Power Knee (PK), a commercially available knee prosthesis. This approach aims to reduce the need for extensive data collection from novel PK users, typically required for achieving state-of-the-art DEP performance.

We hypothesize that:

- Fine-tuned models will outperform models trained exclusively on PK data, successfully transferring walking speed estimation knowledge between domains.
- Fine-tuned models pre-trained on OSL data will outperform those pre-trained on AB data, given the greater similarity in gait mechanics between the OSL and PK user populations.
- Fine-tuning with limited PK data will initially outperform models trained exclusively on PK data, as the transferred knowledge compensates for the smaller dataset. However, as more PK data becomes available, the performance gap will diminish, with both approaches converging after a certain amount of PK data.

These hypotheses aim to explore the advantages of transfer learning in improving model performance and adaptability across different prosthetic devices and user populations.

II. Methods

A. Datasets

This study utilized one natively collected dataset (PK) and two open-source datasets (AB and OSL) to develop a transfer learning framework for walking speed estimation across populations and devices (Fig. 1). The datasets were chosen due to similarities in sensor sets and walking speeds. All datasets were collected in our lab using similar equipment and methods. This study was approved by the Georgia Institute of Technology IRB, and a certified prosthetist

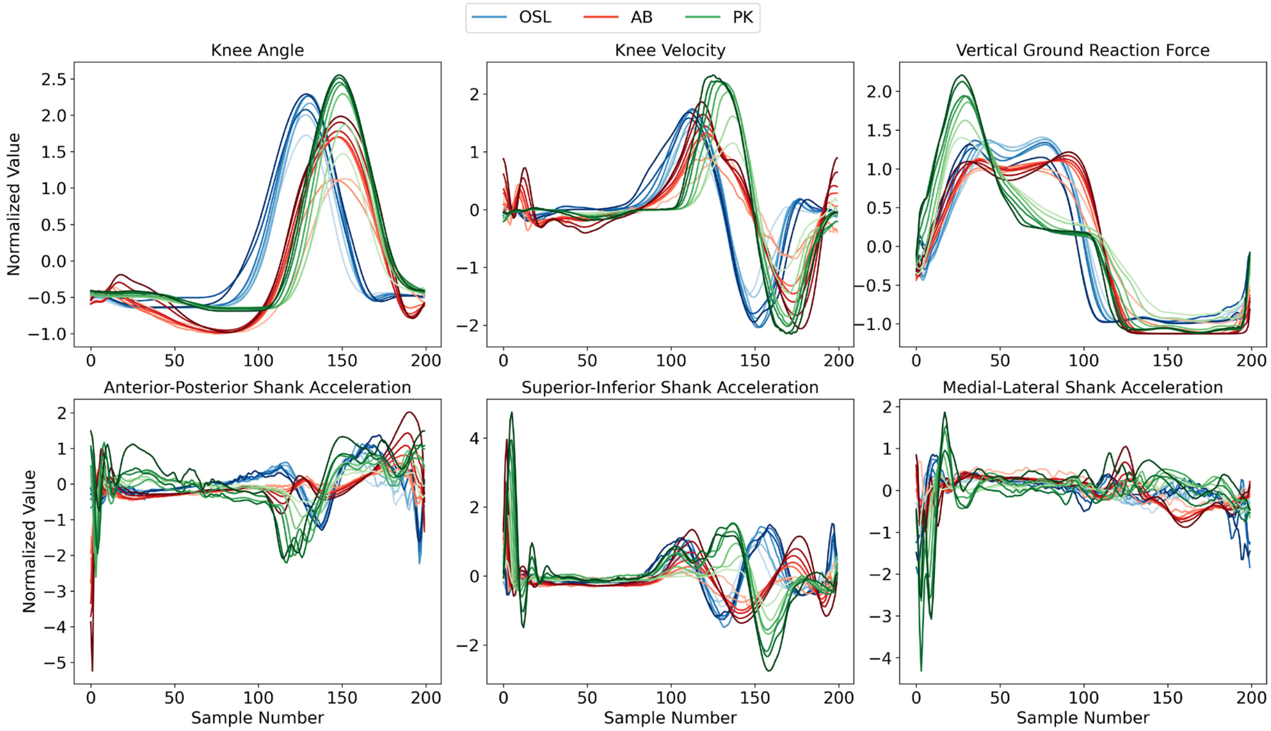

Fig. 2. Sensor signals from individuals with lower-limb amputations using the Open-source Leg (N=9), Power Knee (N=7), and able-bodied individuals (N=20) walking at slow (light) to fast speeds (dark). Raw signals underwent standard normalization, gait cycles segmentation, and resampling to 200 samples. Plotted signals are averages across gait cycles and subjects for each speed ranging between 0.3 and 1.85 m/s.

ensured proper alignment and comfort of the prosthetic devices for each participant.

1) Power Knee Dataset: A total of 7 individuals with transfemoral amputation, wearing an Össur Power Knee prosthetic knee and Veriflex foot, participated in a two-part collection. The collection involved walking at both constant and dynamic treadmill speeds on a Bertec treadmill (Bertec, Ohio, USA). For constant speeds, a 2-minute trial was collected at each speed between 0.3 to 0.9 m/s, incremented by 0.1 m/s. On average, each constant speed trial consisted of 76.8 ± 14.6 prosthesis-side gait cycles, with a duration of 1.71 ± 0.57 seconds per cycle. Two dynamic trials were also recorded. The first followed a staircase profile, holding each speed for 20 seconds before accelerating to the next at 0.1 m/s², covering speeds from 0.3 to 0.9 m/s. The second followed a triangular profile, accelerating from 0.3 to 0.9 m/s and then decelerating back to 0.3 m/s at 0.1 m/s². The Power Knee was equipped with an internal knee encoder, a ground reaction force sensor, and a shank inertial measurement unit (BNO055, Bosch Sensortec, Reutlingen, Germany). A NVIDIA Jetson Nano sampled sensor data from the Power Knee at 100 Hz via serial communication. Treadmill speeds were commanded at 50 Hz by a research desktop running MATLAB. Sensor data and treadmill speeds were wirelessly streamed and recorded on a research laptop using the Robot Operating System (ROS) network. Prosthetic control was managed by proprietary Össur firmware.

2) Open-Source OSL Dataset: A total of 9 individuals with transfemoral amputation, wearing the Open Source Leg (OSL) knee-ankle prosthesis, participated in a collection identical to the PK dataset. The OSL was equipped with an ankle and knee encoder (AS5047P & AK7452 - DEPHY Actpack, Maynard, MA), as well as IMUs on the thigh, shank, and foot (3DMCX5-25 LORD Microstrain, Williston, VT and MPU-9250 InvenSense, San Jose, CA), and a 6-DOF load cell (Sunrise Instruments M3564F, Nanning, China). An NVIDIA Jetson Nano sampled sensor data at 100 Hz via serial communication, which was communicated and recorded along with treadmill speeds (50 Hz) over a ROS network. Prosthetic control was implemented using an impedance-based finite-state machine, which imposed phase-specific prosthetic behavior at each joint, tailored to the preferences of each subject. More details about the dataset are available here: https://doi.org/10.35090/gatech/70300.

3) Open-Source Able-bodied Dataset: A total of 20 able-bodied individuals were equipped with hip, knee, and ankle goniometers (Biometrics. Ltd. Newport, UK); IMUs on the trunk (Yost, Ohio, USA), thigh, shank, and foot; and electromyography (EMG) sensors on their right leg (Biometrics. Ltd. Newport, UK). Six-DOF force plate data were collected using the built-in force plate of the Bertec treadmill. Goniometer, IMU, EMG, and force plate data were sampled at 1000 Hz, 200 Hz, 1000 Hz, and 1000 Hz, respectively. Treadmill walking data were collected at 28 speeds, ranging from 0.5 to 1.85 m/s in 0.05 m/s increments, over 7 trials. Each trial included four speeds, starting from rest, followed by a slow speed, then a medium-fast, and finally a fast speed, before slowing to a medium-slow speed. For example, the first trial involved speeds of 0.5 m/s, 1.2 m/s, 1.55 m/s, and 0.85 m/s, with subsequent trials increasing by 0.05 m/s. Each speed was maintained for 30 seconds to capture steady-state walking. More details about the dataset are available in the associated manuscript [16].

C. Data Processing

To ensure consistency across datasets, we aligned the sensor signals from the PK, AB, and OSL datasets to create a uniform set of inputs for walking speed estimation. The PK dataset consisted of five primary sensor signals: knee angle, vertical ground reaction force (GRF), anterior-posterior shank acceleration, medial-lateral shank acceleration, and superior-inferior shank acceleration. Additionally, a sixth signal—knee angular velocity—was derived by calculating the time derivative of the knee angle (Fig. 2).

To align the AB and OSL datasets with the PK dataset, we retained only the relevant sensor channels, including knee angle, GRF, and accelerations along three axes. Each signal was then transformed to ensure consistency in units and direction across datasets, eliminating discrepancies from differences in measurement systems or coordinate frames. This transformation ensured comparability of the signals across datasets.

Next, data from each subject were segmented into individual gait cycles. The vertical GRF signal was used to detect heel strikes, applying a 20% weight threshold to identify the start of each gait cycle. The data were then resampled to 200 samples per gait cycle, ensuring uniform representation of the gait cycle across different walking speeds. This resampling process standardized the temporal resolution of the data, allowing consistent input for machine learning models.

To further improve consistency, all signals were normalized on a per-subject basis using z-score normalization. This method adjusted each signal by subtracting its mean and dividing it by its standard deviation, producing a distribution with a mean of 0 and a standard deviation of 1. The normalization process reduced inter-subject variability and made signals across datasets more similar. Fig. 2 shows the normalized signals, illustrating the improved alignment between datasets after preprocessing.

C. Model Architecture

The CNN is a deep learning architecture well-suited for capturing feature representations directly from raw sensor signals, eliminating the need for hand-engineered features [17], [27], [28]. Its layered structure enables it to learn complex, hierarchical representations, allowing it to generalize across subjects and achieve robust user-independent performance. In this study, the CNN was applied to estimate walking speed from multi-sensor input data by learning patterns across subjects and speeds.

The model accepted input windows of size 150x6, where 150 represents the number of time samples per window and 6 corresponds to the number of sensor signals (knee angle, knee angular velocity, vertical ground reaction force, anterior-posterior shank acceleration, medial-lateral shank acceleration, and superior-inferior shank acceleration). These windows overlapped, with a new window being fed into the model every 15 samples (~8 Hz) to ensure frequent walking speed updates.

The architecture consisted of three 1D convolutional layers, each followed by a max pooling layer to reduce spatial dimensions and control overfitting (Fig. 1). The convolutional layers used a kernel size of 3 and applied ReLU (Rectified Linear Unit) activations to introduce non-linearity, allowing the model to learn complex feature interactions within the sensor signals. The primary role of these layers was to extract spatiotemporal patterns that are critical for walking speed estimation, particularly given the cyclic nature of gait data. After the convolutional layers, the output was flattened and passed through two fully connected (dense) layers with 128 and 64 units, respectively. ReLU activations were applied in these layers as well, allowing the network to map learned feature representations to walking speed. Dropout with a rate of 0.5 was applied to both dense layers for regularization, preventing overfitting by randomly setting a fraction of the neurons to zero during training. The final output layer consisted of a single neuron with no activation function, as this is a regression problem, and the goal is to predict continuous walking speed values. The model was trained using the Adam optimizer, chosen for its adaptive learning rate properties and efficiency in handling non-stationary objectives. The loss function used is mean squared error (MSE), which is suitable for regression tasks.

This CNN architecture was derived from extensive preliminary optimization, which determined the best input window size, step size (increment), and hyperparameters for walking speed estimation. A key aspect of the transfer learning approach in this study was pre-training the convolutional layers on large, user-independent datasets, which allowed them to learn transferable feature representations. During fine-tuning, the dense layers were adjusted for task-specific adaptation, enabling the model to generalize effectively to new subjects and devices with limited data.

D. Model Training

The model training process consisted of three key stages: pre-training, fine-tuning, and DEP training. This section details each stage, highlighting how pre-trained models were adapted to the Power Knee (PK) data and how DEP models were trained exclusively on PK data.

1) Pre-training: Two models were pre-trained using the AB and OSL datasets to leverage the large, diverse sets of data from able-bodied individuals (AB) and transfemoral amputees using the Open Source Leg (OSL). Pre-training was performed on the full segmented datasets, where data were divided into overlapping windows of size $N\times150\times6$, with N representing the number of windows, 150 being the time samples per window, and 6 representing the number of sensor channels.

During pre-training, the model was trained for 10 epochs with a batch size of 32, using the Adam optimizer and mean squared error as the loss function. The goal was to have the convolutional layers learn generalizable feature representations from the AB and OSL populations. These models are considered user-independent because they are trained on a large number of subjects and expected to generalize well to new subjects in the same population.

2) Fine-tuning: During fine-tuning, the first two convolutional layers of a pre-trained model were frozen, such that additional training with PK data only updated the third convolutional layer and all dense layer weights. The layers chosen to be frozen during fine-tuning were selected based on preliminary optimization of the convolutional layers. Training involved 20 epochs, a batch size of 32, and an early stopping callback set a patience value of 5. Validation data were set to randomly sample 20% of training data. Fine-tuned models are referred to as AB-PK (pre-trained on AB data) and OSL-PK (pre-trained on OSL data).

3) DEP Training: In DEP training, the model was trained exclusively on PK data, with all weights randomly initialized

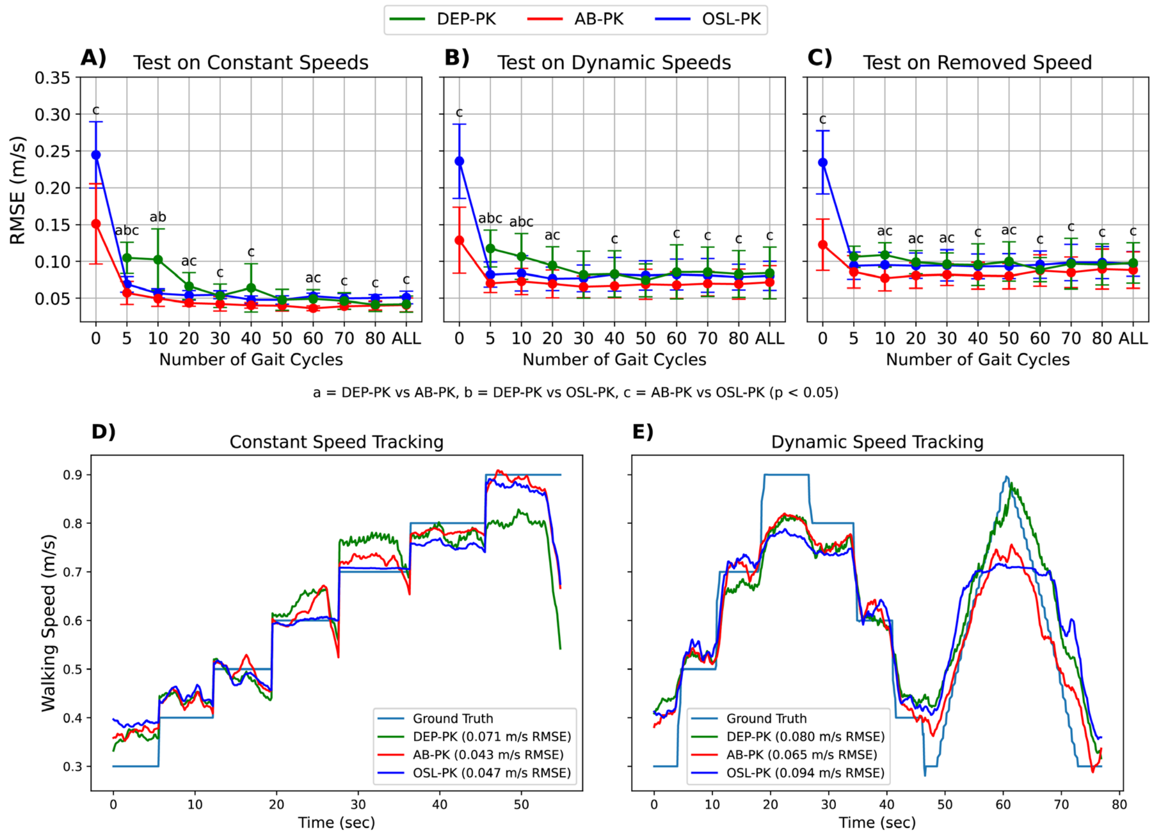

Fig. 3. RMSE trends and tracking performance for AB-PK (red), OSL-PK (blue), and DEP-PK (green) models across different test conditions and gait cycles. AB-PK represents fine-tuning of a model initially pre-trained on able-bodied (AB) data, OSL-PK represents fine-tuning of a model pre-trained on data from transfemoral amputees using the Open-Source Leg (OSL), and DEP-PK represents a model trained exclusively on data from individuals using the Power Knee (PK) prosthesis. Subplots A, B, and C show averaged results from N=7 subjects: A) Test on Constant Speeds evaluates models on 20% of the subject's constant-speed PK data (0.3–0.9 m/s), B) Test on Dynamic Speeds assesses models using all dynamic-speed PK data, and C) Test on Removed Speed evaluates the models on a constant speed excluded from training. Subplots D and E show Constant Speed Tracking and Dynamic Speed Tracking for a single subject using 20 gait cycles for fine-tuning, with estimates filtered using a moving average filter. Error bars in A, B, and C represent standard deviations across subjects. Statistical significance ($p<0.05$) is denoted by letters 'a' (DEP-PK vs AB-PK), 'b' (DEP-PK vs OSL-PK), and 'c' (AB-PK vs OSL-PK).

and no layers frozen. The DEP model learned solely from the available PK dataset, without any prior knowledge transferred from other datasets. This training process was carried out for 20 epochs with a batch size of 32. An early stopping mechanism with a patience of 5 epochs was used to prevent overfitting, and 20% of the data was set aside for validation. Models trained solely on the PK dataset are referred to as DEP-PK.

E. Model Evaluation

The speed estimation performance of AB-PK, OSL-PK, and DEP-PK models were evaluated on both constant and dynamic speeds, using varying amounts of PK data during fine-tuning and DEP training. The amount of PK training data ranged from 0 to 80 gait cycles per speed, including a case where all available PK data (ALL) was used. Walking speed estimates were smoothed using a moving average filter with a window size of 15.

1) Test on Constant Speeds: Models were evaluated on 20% of a subject's constant-speed PK data, meaning that 20% of the data from each constant speed (ranging from 0.3 to 0.9 m/s) was held out for testing. This ensured the models were assessed on unseen data while maintaining a balanced evaluation across all walking speeds.

2) Test on Dynamic Speeds: Models were evaluated using all of a subject's dynamic-speed PK data. This included trials where the subject's walking speed varied in real-time, providing a more real-world scenario for evaluating model performance.

3) *Test on Removed Speed*: In this evaluation, a specific constant walking speed was excluded from the training data to assess the models' ability to generalize to a completely unseen speed. The models were trained on all other speeds and then tested exclusively on the removed speed. This case offers insights into how the models handle interpolation and extrapolation when encountering a previously unseen speed.

The testing strategy focused on assessing the models' ability to generalize across constant and dynamic speeds, with varying amounts of PK data to explore how data availability affects performance.

III. Statistical Plan

Model performance was evaluated across three primary conditions: Test on Constant Speeds, Test on Dynamic Speeds, and Test on Removed Speed. Paired t-tests were conducted to compare the RMSE values between different models for each condition. The comparisons focused on the

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two fine-tuned models (AB-PK and OSL-PK) and the DEP model. Statistical significance was determined at a threshold of $p < 0.05$, and significant differences in RMSE between models are denoted by letters on the corresponding plots (Fig. 3A-C): 'a' indicates a significant difference between DEP-PK and AB-PK, 'b' between DEP-PK and OSL-PK, and 'c' between AB-PK and OSL-PK.

IV. Results

In the Test on Constant Speeds condition (Fig. 3A), AB-PK and OSL-PK without fine-tuning (0 gait cycles) resulted in errors of 0.151 and 0.245 m/s RMSE, respectively (poor performance). After fine-tuning the models with all available PK data (ALL gait cycles), the errors were reduced to 0.041 m/s RMSE for AB-PK, 0.051 m/s RMSE for OSL-PK, and 0.042 m/s RMSE for DEP-PK. The paired t-tests revealed significant differences in error between fine-tuned models and DEP-PK at smaller PK data sets, specifically at 5, 10, and 20 gait cycles ($p < 0.05$). When compared to OSL-PK, AB-PK achieved lower RMSE values across all data amounts, except at 10 and 50 gait cycles ($p < 0.05$).

In the Test on Dynamic Speeds condition (Fig. 3B), AB-PK and OSL-PK without fine-tuning resulted in errors of 0.129 and 0.236 m/s RMSE, respectively. After fine-tuning the models with all available PK data, the errors were reduced to 0.072 m/s RMSE for AB-PK, 0.080 m/s RMSE for OSL-PK, and 0.084 m/s RMSE for DEP-PK. Significant differences in error were observed between fine-tuned models and DEP-PK at 5, 10, and 20 gait cycles ($p < 0.05$). When compared to OSL-PK, AB-PK achieved lower RMSE values for all data amounts except at 30 and 50 gait cycles ($p < 0.05$).

In the Test on Removed Speed condition (Fig. 3C), AB-PK and OSL-PK without fine-tuning showed errors of 0.123 and 0.234 m/s RMSE, respectively. With all available PK data, fine-tuning reduced the errors to 0.088 m/s RMSE for AB-PK, 0.097 m/s RMSE for OSL-PK, and 0.098 m/s RMSE for DEP-PK. AB-PK achieved lower errors than DEP-PK at 10, 20, 30, and 50 gait cycles ($p < 0.05$). In addition, AB-PK outperformed OSL-PK across all data amounts, except at 10 gait cycles ($p < 0.05$).

V. Discussion and Conclusion

Our first hypothesis, that fine-tuned models would outperform models trained exclusively on PK data, was confirmed. Both AB-PK and OSL-PK models significantly outperformed the DEP-PK model at smaller data amounts, especially when fewer than 30 gait cycles of training data were available. This suggests that transfer learning successfully transferred walking speed estimation knowledge between domains, allowing the fine-tuned models to achieve lower errors with less data.

The second hypothesis, that fine-tuned models pre-trained on OSL data would outperform those pre-trained on AB data due to greater similarity in gait mechanics, was not supported by our findings. In fact, across both constant and dynamic speed conditions, the AB-PK model generally outperformed the OSL-PK model in the vast majority of cases. The more extensive AB dataset may have captured generalized walking patterns that transferred more effectively during fine-tuning, even when applied to a population with different gait mechanics. This finding underscores the utility of AB data in transfer learning for prosthetic applications, even when the target population involves amputee gait.

The third hypothesis, that fine-tuning with limited PK data would initially outperform models trained exclusively on PK data, with the performance gap diminishing as more PK data became available, was confirmed. As hypothesized, fine-tuning with limited PK data led to better initial performance compared to DEP models trained solely on PK data. However, as more PK data became available, both approaches began to converge, with the performance gap diminishing, especially after 50 gait cycles, supporting the idea that transfer learning compensates for smaller datasets in the early stages of training.

The Test on Removed Speed condition provided further evidence of the utility of transfer learning. AB-PK consistently outperformed OSL-PK across most data amounts, further demonstrating the strong generalization capabilities of the AB-PK model on unfamiliar speeds.

Taken together, the models pre-trained on AB data exhibited strong generalization capabilities, even when fine-tuned with small amounts of PK data. While OSL-PK performed comparably, AB-PK's access to a larger, more diverse dataset may have provided a more robust starting point for fine-tuning. In a comparable set of experiments with DEP models, Bhakta et al. [17] reported RMSE values of 0.014 m/s for constant speeds, 0.067 m/s for dynamic speeds, and 0.034 m/s for speeds excluded from training. Non-machine learning studies involving lower-limb prosthetics achieved RMSE values of 0.09 [20], 0.10 [15], and 0.036 [29] m/s. Specifically, our lowest post-fine-tuning RMSE values for AB-PK were 0.041 m/s for constant speeds, 0.072 m/s for dynamic speeds, and 0.088 m/s for excluded speeds. This discrepancy is likely due to the reduced sensor set used in our study. Bhakta et al. employed a knee-ankle prosthesis equipped with a more comprehensive sensor suite. Nonetheless, the AB-PK model demonstrated strong performance despite the limitations in sensor data, underscoring the robustness of transfer learning in this application.

The results provide key insights into model performance, the effectiveness of transfer learning across different populations (able-bodied vs. amputee) and prosthetic devices (OSL vs. PK), as well as the amount of data required to achieve high accuracy. This has significant implications for real-world prosthesis control systems. By incorporating transfer learning into the model development process, practitioners can minimize the amount of user-specific data required to achieve high-performing speed estimation. This approach could reduce the burden of data collection for new prosthesis users, making it easier to personalize prosthetic devices and improve user experience.

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VII. References

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