2023 International Symposium on Medical Robotics (ISMR)
Atlanta, GA, USA, April 19-21, 2023

Adaptive Lower-Limb Prosthetic Control: Towards Personalized Intent Recognition & Context Estimation

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***Abstract*—Historical advancements in lower-limb prostheses have reflected the challenges of diverse anthropomorphic biomechanics, limiting intelligent control systems from being implemented and reflecting true user intent. With recent advancements in machine learning (ML), however, this notion is being challenged. In transfemoral-powered prostheses, time series information has been used to infer context (slope angle and walking speed) and intent (ambulation mode) and scale torque assistance accordingly in real time. In this study, we build off this work by proposing and validating a real-time framework for adaptive walking speed context estimation. Our system makes use of the general similarity in human gait patterns and iterates subject-independent ML models used for prediction towards subject-dependent models by method of batched retrospective labeling and retraining. Offline validation for walking speed estimation has been completed using seven amputee subjects' data, showing an average subject-independent MAE of 0.063 being reduced to 0.043 m/s, a 31.7% improvement. In addition, we discuss and present preliminary results for walking speed estimation and several alternative methods of retrospective labeling.**

Index Terms – Lower-limb prosthetics, biomechanics, machine learning, context estimation, intent recognition.

I. Introduction

With over 2 million limb amputees in the U.S. alone – a number growing by approx. 185,000 a year – the need for prostheses that enable the continuation of day-to-day activity is clear [1]. Often, however, powered lower limb prostheses necessary to enable this behavior lack sufficient control systems to distinguish them from those of passive systems, which often struggle to simulate natural gait patterns and improve user ambulation. [2]. In recent years, developments in embedded and control system design have begun to change this. Microprocessors that imitate the walking patterns of users can now incorporate real-time high-level processing of sensor data, which are located on powered knee-ankle prostheses [3], [4]. These powered prosthetic devices address the asymmetries that can result in gait in a person with an amputation using passive systems [5]. Additionally, powered prosthesis devices offer an array of other benefits such as decreased hip work and power generation from the affected limb, decreased metabolic expenditure, improved user satisfaction with walking speed and distance, and decreased frequency of falls when using a powered prosthetic device [6]. With the goal of restoring intent recognition to the amputee in and out of clinical settings, we consider signals from kinematic and mechanical, rather than neural-interfacing, sensors. This is due to the high level of unreliability – especially over time – that electromyography (EMG) sensors exhibit from surface shifting, sweat interference, etc. as well as high inter-subject variability [7], [8], whereas kinematic and mechanical sensors allow for better tracking accuracy and information transmission that enable more better subject-invariant measurements [8].

In this study, we use inertial measurement units (IMUs), loadcell, and encoder data to indirectly predict mode classification, walking speed, and slope angle regression [10], [11], [12]. This process, called *forward prediction*, is a key feature of our proposed system, and many techniques, including numerical methods such as integration techniques and machine learning algorithms like convolutional neural networks (CNN) [13] and XGBoost models [14], [15], have been used to develop effective forward predictors. The forward predictor's speed estimates are used to calculate torque scaling coefficients to modify the behavior of the knee and ankle joints on the prosthesis [16]. Torque scaling is essential for natural motion of the subject's gait due to changing biomechanics with walking speed [17]. Although past studies have successfully identified user intent for classifying locomotion modes [13], [15], we focus specifically on user walking speed estimation and have chosen to develop a novel CNN-based forward predictor for real-time processing rather than computationally expensive feature extraction [15]. This choice allows us to explore deep networks and their fit within our proposed adaptation pipeline.

Using static forward predictors alone, reasonably low error rates are attainable. However, it is unlikely that these error rates will improve over time or across different individuals. Therefore, the models can be considered *subject-independent*, which naturally leads to our proposed system design. This contrasts with a subject-dependent model which are trained exclusively using data from subject they are intended for [18]; however, in our framework, the predictors tend towards a subject-semi-dependent model, utilizing both general knowledge of human gait patterns and continuous integration of subject-specific data.

Similar to [19], we approach the problem by using a periodic retraining cycle of the forward predictors using labels that are retrospectively assigned by slower, yet more accurate models (which we will refer to as *backwards estimators*) that look at past gait data to iterate the forward predictors towards *subject-dependent* efficacy. The backwards estimators benefit not only from a more lenient computation timeline but also from completed raw user stride data.

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2023 International Symposium on Medical Robotics (ISMR) | 979-8-3503-0162-5/23/$31.00 ©2023 IEEE | DOI: 10.1109/ISMR57123.2023.10130251

Previous works have successfully shown the viability of an adaptive intent recognition algorithm that can improve as the user ambulates by using real-time neural and mechanical sensor data to continuously update a forward predictor [19], [20]. These works have primarily focused on detecting and classifying the user's ambulation mode through feature-extracted data fed into ML classifiers. This paper proposes an alternate application of the adaptation algorithm that can be used specifically for context estimation (i.e., walking speed estimation) while using a forward and backward estimator that can make regression estimates with raw sensors, eliminating the need for a feature extraction process. Overall, we expect the adaptive framework to improve the forward predictor's speed estimations by using real-time sensor data from the prosthesis to retrain itself and ultimately develop a model that is unique to each user.

II. Methods

A. Open Source Leg (OSL) & ROS Communication

The prosthesis used in this paper was the Open Source Leg (OSL) developed by the University of Michigan and constructed by The Exoskeleton and Prosthetic Intelligent Controls (EPIC) Lab at Georgia Tech [21], [22]. The powered knee-ankle prosthesis consists of a six-degree-of-freedom (DOF) loadcell, three six-degree IMUs (thigh, shank, and foot), two joint encoders, and two actuators, one for each joint. A Raspberry Pi 4 was used for computing real-time ML context estimation and an external computer was used for communication with the Pi and for assistance tuning in real time.

The control architecture for the prosthesis is divided into three levels: high, mid, and low. The high-level control is responsible for detecting user intent (mode classification) and making context estimations (walking speed, slope angle regression) using onboard sensor data and pre-trained ML models. The mid-level controller consists of a finite state machine (FSM) where the transition between ambulation modes and between gait phases are managed with the movement parameters of the knee and ankle joints. The desired joint torques are calculated by

$$\tau_i = -k_i(\theta_i - \theta_{ei}) - b\theta_i' \quad (1)$$

where i, θ_i, and θ_i', are the joint in question, angle, and angular velocity given by onboard encoders, respectively, k is the stiffness, b is the damping coefficient, and θ_{ei} is the target angle specified by the FSM [23].

The context estimations from the high-level controller are continually preprocessed with a Kalman filter. This is a common filter used to infer more accurate estimates of unknown variables by recursively estimating the joint probability distribution over the variables for each timeframe [24]. In this case, it decreases the likelihood of undesired joint movements which would be unexpected by the user and cause stumbles. The filtered context estimates scale impedance parameters that produce desired torque values from (1), which are then processed by low-level controllers and passed onto the actuators with built-in PID controllers for delivering the desired scaled assistance to the leg.

The method of data communication between different concurrently running nodes such as the FSM and forward predictors is handled by ROS which broadcasts channels such as sensor data, current phase, mode, and ground truth labels which are all used by the adaptive pipeline. The adaptation then learns the subject-specific gait patterns and progressively improves the models used to predict context estimations in real time.

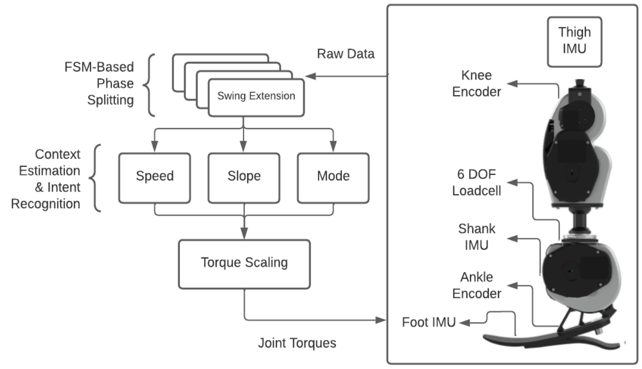

Figure 1. OSL sensors, control structure, intent recognition, and context estimation.

B. Backwards Estimator

The backwards estimator is a key component of the adaptive pipeline that impacts the effectiveness of the overall adaptive model. While various methods of backwards estimation can be implemented, it is essential to choose the method that can reliably produce estimations with errors less than that of the forward predictor. Because the backwards estimator looks at a larger window of data and the accuracy of the estimate is more integral than the speed of estimation, more numerical methods are considered alongside ML frameworks. The following methods were explored offline in determining user walking speed.

TABLE I. TCN Architecture and Parameters

Hyper Parameter	Speed Estimator
Kernel Size	10
# Channels / Hidden Layer	10
# Levels	3
Dropout Probability	0
Learning Rate	1e-4

i) Temporal Convolutional Network (TCN)

A deep learning backwards estimator framework that we evaluate is a TCN. This model used an architecture and hyperparameter tuning procedure identical to that used to estimate hip moment in [25]. The selected parameters are shown in Table 1. For the scope of this paper, only the speed estimator parameters are relevant.

ii) XGBoost

Another ML approach to context estimation is through XGBoost, a gradient descent algorithm that minimizes its loss function by forming and combining the estimations of smaller regression trees [16]. Each subsequent tree is used to predict the error of the previous tree with a penalty function to prevent overfitting. The feature inputs were manually optimized through a feature extraction process that calculates 128 features found to be relevant to stride dynamics using 50ms segments of raw data from the 28 sensor channels of the OSL. In constructing the model, the standard optimization procedure from our previous studies was used [26]-[28]. For this study, four separate models for each gait phase (i.e., ES, LS, SF, SW) were used.

iii) IMU

The user's walking speed can be estimated using simple physics-based methods. A foot IMU (RT-BLE-001 r3) from Navigation Solutions LLC was used in this study, with data collected on a Raspberry Pi Zero for offline analysis. An able-bodied subject walked on a level treadmill at speeds ranging from 0.3 to 0.9 m/s in increments of 0.1 m/s, with the speed estimated by calculating the Euclidean distance between consecutive heel contact points and dividing by the time elapsed. Trials were repeated with the IMU attached to the foot of the OSL, and the same subject wearing the OSL to simulate a person with transfemoral amputation.

iv) Filtering

Due to noise in sensor data, raw context estimation values are also very noisy. While ambulation mode is qualitative in intent recognition, walking speed and slope angle estimates are quantitative and small differences in their values directly impact the amount of scaled assistance provided by the actuators. As a result, it is important to filter the raw estimations to be more accurate and ensure a natural gait. In real-time applications, the Kalman filter has been the best fit for filtering data from onboard sensors on the OSL to help predict the user's next step, but it is not strictly beneficial when used in conjunction with the backwards estimator which relies on data that has already been collected. Specifically, one major downside of real-time filters is phase lag [29], [30]. Regardless of how well the filter performs, the filter cannot instantly react to a sudden change in incoming data because it requires time for the signal to reach the filter. As a result, a zero-phase filtering method, which processes input data both in the forward and backwards direction, is used to mitigate phase shifts in the signal during filtering. Another method is using a Savitzky-Golay filter (Savgol), which finds the best-fitting low-degree polynomial with a sliding window to smoothen out the signal [31]. In the offline analysis, we evaluate the performance between these different filtering methods.

C. Forward Predictor

The forward predictor used in this study was a four-phase CNN. Similar to the backwards estimator XGBoost model, individual models for each phase were used to reduce any error introduced by the sensor characteristic differences seen between phases. The overall architecture of the CNN was identical between the four phases, with parameters and layers optimized through a hyperparameter sweep. The optimized model of a single 1-D convolution layer followed by a flatten layer, two dense layers, and outputs a single estimation value.

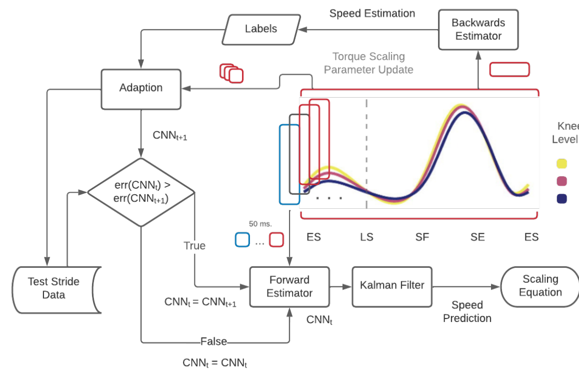

Figure 2. Adaptive pipeline schematic showing data flow to backwards estimator (evaluated every three strides) and forward predictor (evaluated every 50ms.).

Each CNN takes in 50ms of data, with 25ms of overlap between consecutive windows of data.

D. Adaptive Pipeline

As shown in Fig. 2, our approach has both the forward predictor and adaptive processes acting in parallel. The raw sensor data from the OSL are continuously extracted in 50ms. windows and used to produce real-time intent predictions which are, in turn, used to scale torque. Upon the completion of each three-stride batch, the backwards estimator retrospectively processes the completed gait data and produces more confident labels for walking speed. Using the resulting labels and gait data for the first and third stride in the batch, we update the forward predictor models for each phase. Using the labels and data associated with the second stride, the pipeline compares the error rates of the currently used forward predictors with the updated models, iterating the operational forward predictors with the superior of the two for each category and phase.

Although evaluated offline, the pipeline is designed to function in real-time experiments. As such, the sensor data collected is broadcasted as a message on the ROS network at 100 Hz and processed by a distinct node that alerts the main adaptation scripts upon the completion of each stride. The adaptive pipeline then proceeds as described above and broadcasts the updated forward predictor model parameters to a separate node that handles real-time context predictions.

To integrate the forward predictor and backwards estimators into a logical framework, we must consider several design choices. First, we chose to use a three-stride-long retrospective window so that the update times would be relatively short, yet still fit within training time restrictions. The organization of data from these windows into train-test-train sets minimizes the temporal similarity of test sets while ensuring that the majority still supplies the training pool.

There is also the question of how to update the models. We chose to do this completely disjointed – every model for mode (e.g., Level Walking) and phase (e.g., Early Stance) is updated separately – based solely on error rates. This ensures that the error will only trend downward for all evaluation metrics, rather than requiring universal improvement across each mode and phase to meet the criteria for updating.

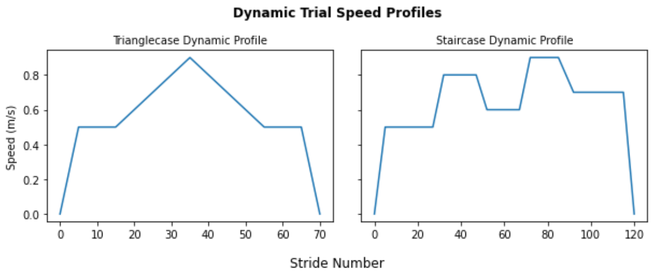

Figure 3. Dynamic trial treadmill speed profiles.

The adaptation was completed using a stochastic gradient descent optimizer with a 1E-3 learning rate, 300 epochs, a batch size of 32, and by freezing all convolutional layers.

E. *Offline Analysis*

The subjects each underwent a two-part trial: walking at static speeds (0.3 m/s to 0.9 m/s with 0.1 m/s discontinuous increments) and dynamic speeds on a treadmill, where the dynamic speed profiles followed triangle case and staircase profiles (Fig. 3) with the speed being varied over the duration of the trial. The subjects averaged 171 strides (STD 21), approximately 80% of which were in static speed profiles. We used stride data collected from seven transfemoral amputee subjects to evaluate the performance of our pipeline. Before running the offline analysis, the subject-independent models were trained for the forward predictors in a modified fashion. Rather than training on the entire set of data, we trained seven distinct sets (ES, LS, SF, SE) of models, where set *i* was trained on all data but that of subject *i*, then evaluated through adaptation on subject *i*. This ensured that we were measuring the accuracy in the transition from subject-independent to subject-dependent models.

Additionally, to simulate the error introduced by the IMU-based backwards estimator (0.03 m/s MAE able-bodied, 0.06 m/s MAE able-bodied wearing the OSL), we ran a trial adapting on ground truth labels with an average of 0.05 m/s MAE noise introduced, which was the best error rate of all methods studied.

III. Results

A. *Backwards Estimator*

The backwards estimators were evaluated offline with the ML models having a similar offline analysis approach as the forward predictor. The filtering methods were evaluated on the raw TCN signal as shown in Fig. 4. When comparing the ML approaches, the TCN is seen to outperform the Kalman-filtered XGBoost regression by MAE of 0.019 m/s. When the ground truth value makes a step change, there is evident lag seen in the Kalman filtered estimates. The zero-phase Kalman filter mitigates that signal lag, allowing the estimations to track the ground truth labels more accurately. The zero-phase Kalman filter performed similarly to the Savgol filter. The IMU method's estimations were significantly better than the other methods, with an average MAE of 0.030 m/s across trials on an able-bodied subject and 0.060 m/s with the OSL on the same subject. Overall, the IMU tested on an able-bodied subject without the OSL had the lowest average error of 0.030 m/s, an 66.7% improvement over the forward estimator.

a)

b)

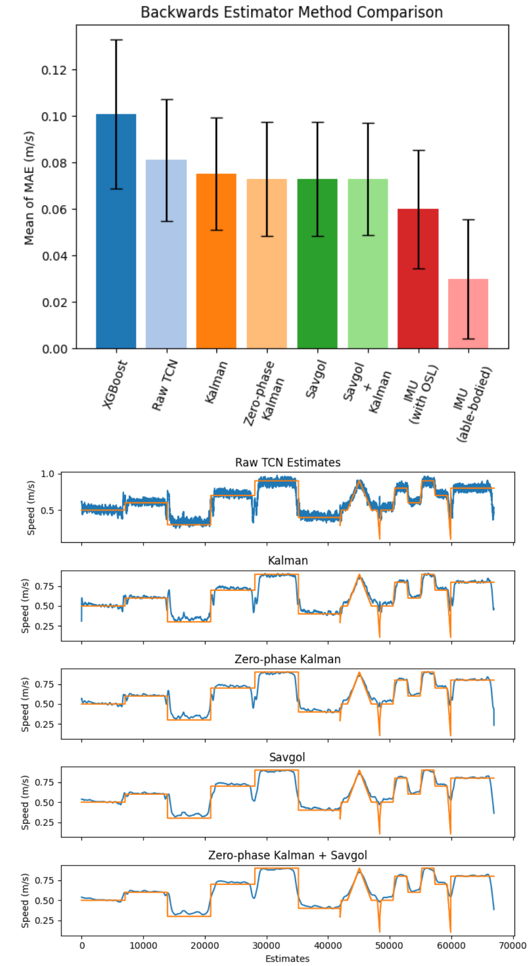

Figure 4. (a) Backwards estimator average MAE comparison. MAE = [0.101, 0.081, 0.075, 0.073, 0.074, 0.074, 0.060, 0.030], STD = [0.032, 0.026, 0.024, 0.024, 0.024, 0.024, 0.026, 0.026] m/s. (b) Filtered TCN estimations with different filters. The orange line is the ground truth values.

B. *Adaptive Pipeline*

The adaptive pipeline was evaluated on seven different subjects, the predictions of two of which are shown in Fig. 5. Although tracking the ground truth values more tightly, the adapted models seem to exhibit more outlier values, especially in the TF1 trial. On average, the MAE was reduced from 0.0631 (STD 0.0189) m/s in the subject-independent models to 0.0430 (STD 0.0065) m/s after adaptation. Additionally, all subject trials proved the adaptation to be superior and, as seen in Fig. 6b, the adapted MAE is consistently lower than the independent models. The several spikes seem to correspond to transitions between static walking speeds which could potentially be attributed to poor adaptation to irregular stride patterns.

IV. Discussion

Results from the backwards estimation models show the TCN to be preferable over XGBoost and numerical approaches with lower error. To further improve the TCN

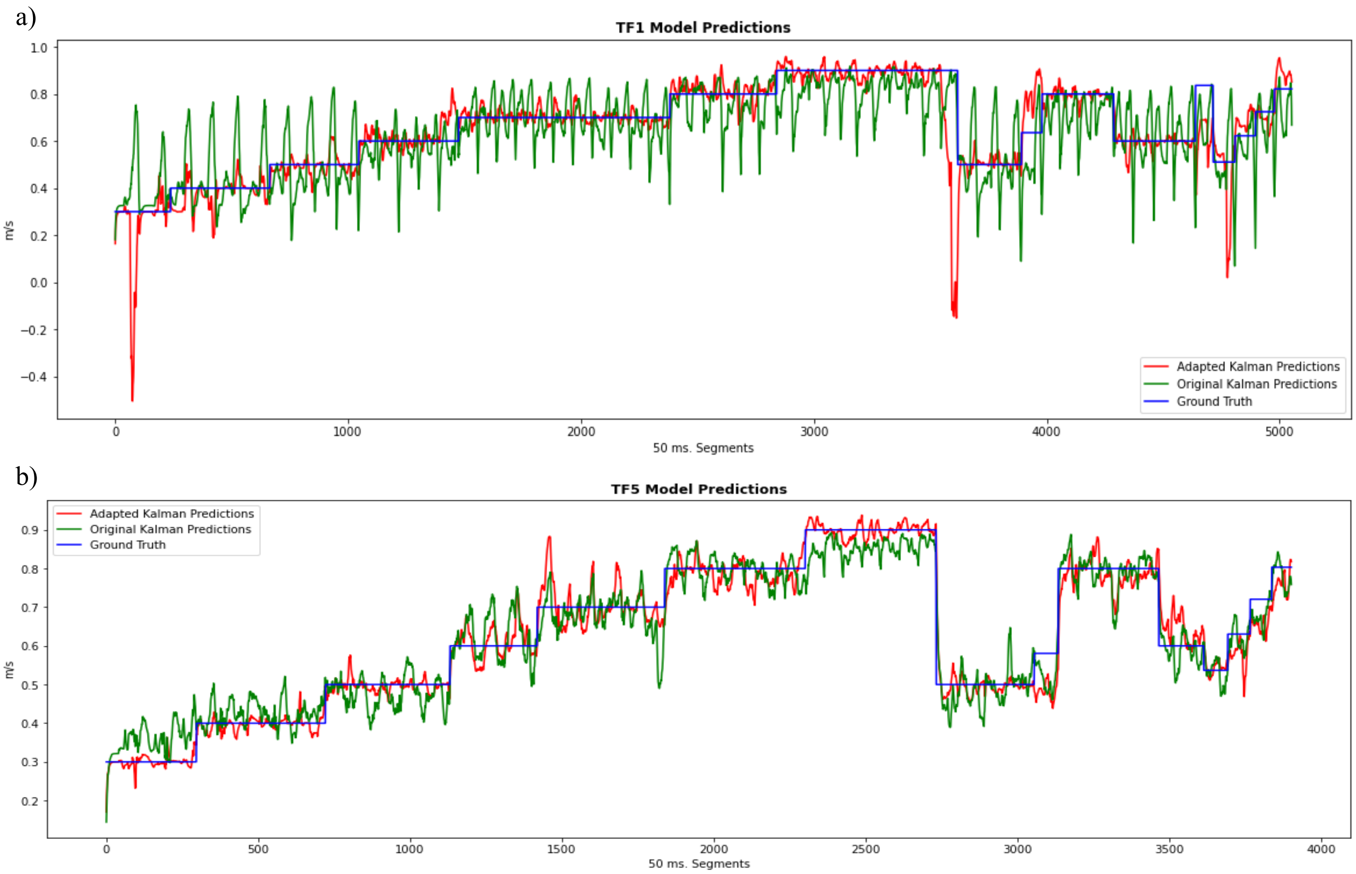

Figure 5. (a) TF1 and (b) TF5 adaptation predictions.

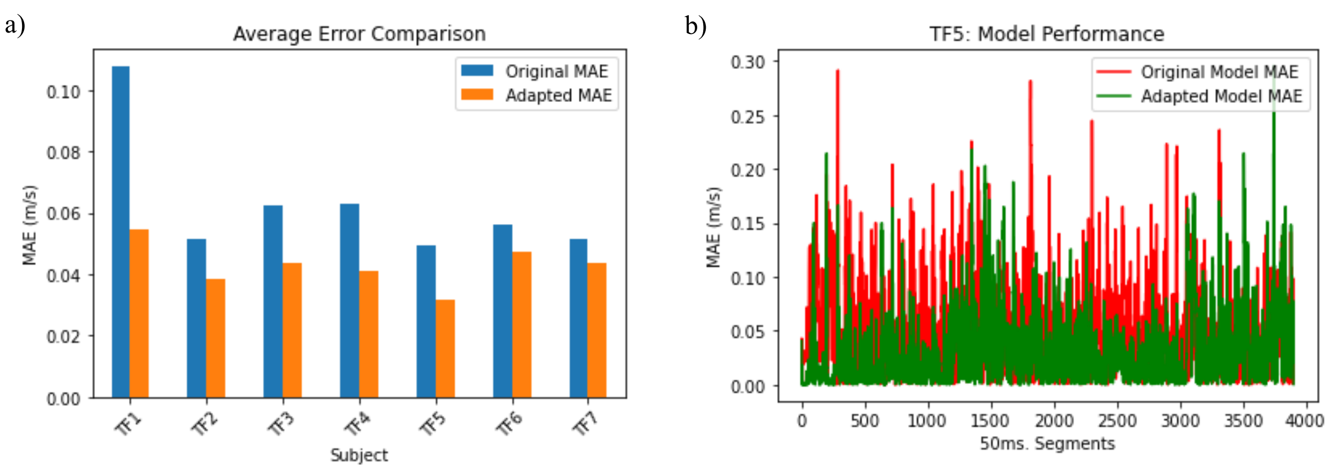

Figure 6. (a) Subject MAE comparison. (b) TF5 MAE vs. model iteration.

estimations, filtering is necessary. While it was hypothesized the zero-phase filter would significantly improve the errors due to phase lag, the reduction in error was not substantial. Although the estimations are able to react to the instantaneous changes in walking speed faster, the majority of the error is attributed to noisy peaks in the estimations. A Savgol filter was applied on the zero-phase Kalman filter output, which smoothened out the prediction, but was not able to remove all peaks. To improve this, a larger window of evaluation for the Savgol filter can be used. However, while this will smoothen the noise further in regions of relatively constant speed, it will worsen estimations when the speed varies due to underfitting. Future work may investigate other methods of filtering, such as an adaptable Savgol filter with a window size that varies with the variance in signal data. Overall, the IMU method was determined to be the best method. While we only tested on an able-bodied subject using the OSL, we expect the performance to be similar for a transfemoral subject with the OSL. In addition to the lower average MAE, the numerical IMU method is computationally less demanding than other ML methods and can also produce better estimations with less time.

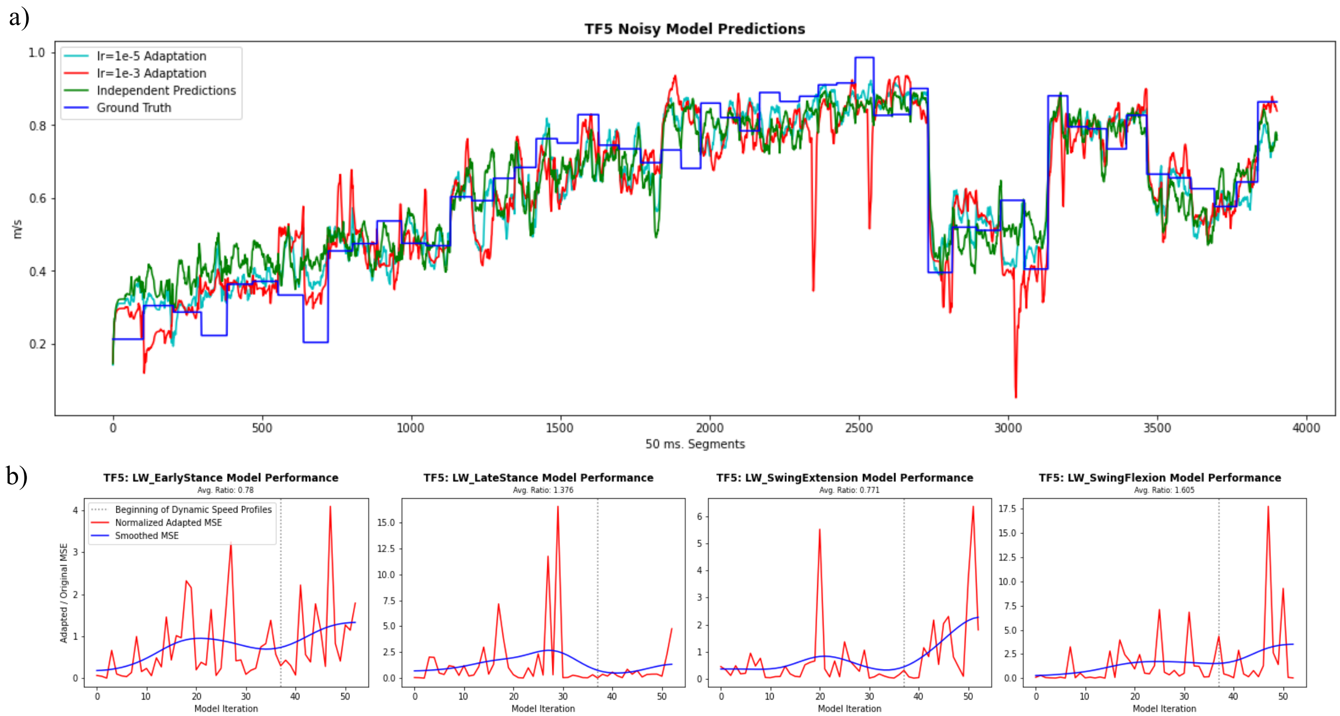

Figure 7. (a) TF5 adaptation with 0.05 MAE noise introduced. (b) Normalized MAE vs. model iteration.

As seen in Fig. 7a, by introducing 0.05 MAE to the ground truth signal, the adapted MAE decreased to approx. 0.0747 m/s and the independent MAE to approximately 0.0714. We also adapted with a lower learning rate of 1E-5, rather than 1E-3, and repeated the TF5 noisy trial. This resulted in a decrease from 0.0747 to 0.0661 m/s MAE, improving the previously superior independent model. Overall, the adapted walking speed estimator is able to outperform the original, non-adapted model.

Fig. 6a demonstrates a consistent performance of the adapted model across subjects, regardless of the independent model's performance. The average MAE improves, and the standard deviation decreases by 65.6% from 0.0189 to 0.0065 m/s, as observed when comparing MAE with and without adaptation. While TF1 exhibits significantly higher error without adaptation, with adaptation, the MAE reduces to levels comparable to the other subjects, indicating the pipeline's ability to reliably adapt to the subject over time, even when the subject has abnormal gait characteristics.

However, the pipeline's major weak point is the transition between static and dynamic walking speeds, as seen in Fig. 7b. The adaptive error relative to the independent error rates rapidly increases at the beginning of dynamic trials, particularly for Early Stance and Swing Extension models. This may be due to the models learning to overshoot the ground truth, resulting in several outlier data points in Fig. 7a. Furthermore, poorer estimation on datapoints (such as .2-.4 m/s in the beginning of the dynamic trials) is expected. To counteract this, one potential approach is to temporarily reduce the learning rate used when retraining the forward predictor when dynamic data is detected, handicapping the model's ability to make drastic changes.

To improve computational speed and accuracy, updating the running test set could involve randomly selecting a fixed number of completed strides from the entire test set and evaluating new models with the restricted set. This approach also allows for outlier test strides to be removed using a peak filter, which reduces the likelihood of models adapting to inaccurate backwards estimates.

V. Conclusion

This study proposes an adaptive framework for walking speed estimation that can adapt a user-independent ML model to the user. We achieved an average MAE improvement of 0.02 m/s with a phase-based CNN forward estimator that updates itself every three strides using a ground truth speed label, over a user-independent CNN estimator that does not adapt with user ambulation, proving that adaptation for context estimation is viable. The significant improvement in STD also prove that the final adapted model has cross-subject reliability, where the model's performance is consistent regardless of the user. The proposed framework could potentially be applied to other areas of locomotion outside of speed as well, such as mode classification and slope estimation, and while the paper used a CNN, the same framework can be applied to estimators with different models with similar improvements to be expected. Various methods of backwards label estimators were explored as well, and numerical methods based on IMU data had the lowest average MAE error of 0.060 m/s. In the future, the framework should be validated in real-time with adaptation performed with labels provided by the integrated backwards estimators.

Acknowledgment

We appreciate the contributions of all participants in this study, as well as the expertise and resources provided by EPIC Lab at Georgia Institute of Technology.

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