# A Task-Agnostic Approach to Unified Multi-Activity Gait Phase Estimation via Bilateral Sensing

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***Abstract*— Estimating the gait phase is a key aspect for controlling many lower-limb rehabilitation robots, including transfemoral prostheses. Current control approaches often rely on high-level activity classification to then employ a task-specific phase algorithm, which can limit adaptability across tasks and introduce risks associated with misclassification. This study proposes a novel unified phase variable framework with two approaches, one using activity classification and one being entirely task-agnostic. The framework uses predicted gait event information to continuously define a unified phase variable across level walking, ramp ascent/descent, and stair ascent/descent at various inclines and speeds. The classification approach senses the unilateral thigh angle, whereas the task-agnostic approach expands sensing to include the contralateral thigh angle. Simulated evaluations using an able-bodied dataset demonstrate average phase root-mean-square error of 6.8% with classification and 6.3% in the task-agnostic mode. The bilateral task-agnostic approach notably performed the same or better than the unilateral classification-based approach, showing improved consistency across subjects and tasks, particularly during stair ascent. These results highlight the feasibility of task-agnostic gait phase estimation for prosthesis control, demonstrating performance comparable to task-specific models while removing reliance on activity classification.**

## I. Introduction

Robotic lower-limb prostheses offer great potential to improve the mobility and quality of life for individuals with lower-limb amputation, but reaching this potential could be largely dependent on the selected control approach. Several prosthetic controllers have been developed for effective level-ground walking [1], [2], demonstrating more normative joint biomechanics [3], less energy expenditure [4], and potentially more endurance [5] when compared to passive prostheses. While these benefits highlight the potential of these devices, it is critically important to develop control algorithms that are also effective across a wide range of activities of daily living (ADLs).

Research focus has shifted to controlling activities beyond level walking, including ramp walking [6]–[8], stair climbing [9], [10], sit/stand activities [11], [12], and even non-standard activities [13]–[15]. The prevailing approach to enabling multi-activity prosthesis control is to employ a high-level task classifier to determine the user's desired activity, and then discretely switch between mid-level controllers with task-specific properties [16], [17]. Several classification approaches in lab settings have achieved accuracy rates greater than 99% [18]–[22], which could enable users to receive the benefits from powered prostheses during several ADLs. However, even infrequent misclassifications leading to the deployment of the wrong mid-level controller could cause negative consequences such as falls. Furthermore, classification approaches require a limited, predefined set of activities, usually leaving many possible tasks (e.g., continuous variations of a predefined task) unaccounted for.

More recently, there has been increasing interest in task-agnostic control approaches that do not require any knowledge of the intended activity. Broadly speaking, there are two primary perspectives for pursuing task-agnostic control: Machine Learning (ML)-based and biomechanical model-based frameworks. ML-based control approaches that account for multiple ADLs without classification often use neural networks (NNs) to map directly from kinematic inputs to joint level outputs such as torque [23]–[26]. These approaches offer high theoretical promise but have demonstrated several associated limitations, including sensitivity to the training data such as bias towards level walking, the potential for unexpected behavior when encountering out-of-distribution inputs, and reduced interpretability, all potentially limiting clinical and commercial acceptance.

The second approach to task-agnostic prosthetic control is to impose some level of structure based on typical human locomotion biomechanics. Incorporating these principals into the model structure could make this framework more robust and interpretable when continuously spanning multiple locomotion tasks. These model-based, multi-activity control methods include heuristic control laws [27] or continuous phase variables that monitor the progression of gait [8], [28]. The ability to continuously monitor gait progression (gait phase) is a key element to many model-based approaches, and has also been used for bipedal robot control [29], exoskeleton control [30], and clinical gait analysis [31].

A phase variable can be defined as a biomechanical parameter that indicates the phase progression from the beginning to end of a locomotion activity, which is typically cyclic in nature. Candidate phase variables have included the center of pressure (for stance progression only) [2], tibia kinematics (typically for prosthetic ankle control) [32], [33], and various hip/thigh kinematics (common for knee-ankle control) [34]. These phase variables support different control architectures including position control [2], [6], [28] and impedance control [7], [8], [33], and they have been used in both model-based and ML-based approaches [35], [36]. In [36], an ML-based, multi-activity phase estimation approach is presented

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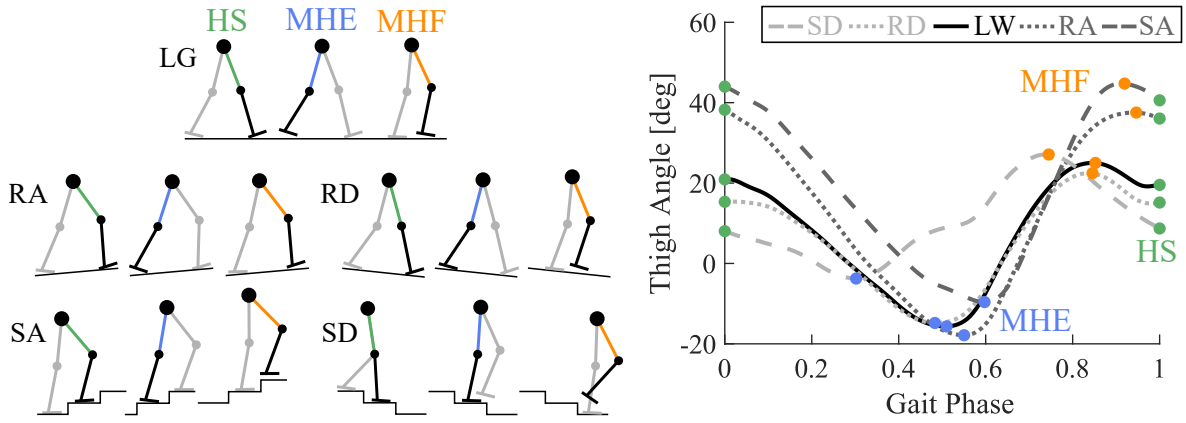


Fig. 1. Left: Gait events of heel strike (HS), maximum hip extension (MHE), and maximum hip flexion (MHF) are each observed in locomotion tasks of level walking (LW), ramp ascent (RA) and descent (RD), and stair ascent (SA) and descent (SD). Right: The corresponding gait phase and thigh angle magnitude of these gait events changes based on locomotion task.

for exoskeletons, but is not shown to generalize to varying speeds, ramp inclines, or stair heights. Model-based phase variables typically have task-specific definitions (e.g., differing definitions for walking and stair climbing tasks [9]) and thus rely on accurate task classification. There is currently no model-based phase variable definition that is unified across the primary ADLs, which limits the development of more robust and interpretable task-agnostic control approaches.

Therefore, in this work, we present a novel piecewise-monotonic phase variable framework that maintains a unified definition across level walking, ramp ascent/descent, and stair ascent/descent at several different inclines and speeds. The contribution herein includes two novel phase model definitions: 1) a unified phase variable based on unilateral thigh sensing that maintains the state-of-the-art task classification structure, and 2) one based on bilateral thigh sensing that is entirely task-agnostic. Both of these definitions represent the first model-based phase variable that is structurally unified across these primary ADLs. By simulating with an able-bodied dataset [37], the effectiveness and potential of these approaches are demonstrated with an overall phase RMSE error of 6.8% with classification and 6.3% when task agnostic. These results suggest that this unified phase variable could be a promising component of seamless prosthesis controllers across locomotion tasks that can be incorporated in a variety of control frameworks.

## II. Unified Gait Phase Estimation

### A. Piecewise Phase Variable Definition

As in or previous work [8], [9], [38], the phase variable is estimated from the global thigh orientation in the sagittal plane, which can be measured by an inertial measurement unit (IMU) onboard the thigh segment of the prosthesis. The piecewise phase variable, as first proposed in [39], structures the phase estimation with a finite-state machine (FSM), consisting of generally monotonic thigh trajectory regions. A key observation when adjusting for task unification is that the primary tasks of level walking (LW), ramp ascent (RA) and descent (RD), and stair ascent (SA) and descent (SD) all share an initial descending thigh orientation section, followed by an ascending thigh orientation section, and ending again with a descending section (Fig. 1). These three sections define the three states of the FSM (S1, S2, and S3).

Forward progression through this state machine can be defined by key gait events: 1) heel strike (HS), defined as initial foot contact with the ground, triggers the transition to S1; 2) maximum hip extension (MHE), defined as the minimum detected thigh angle for a given stride that occurs after HS, triggers the transition to S2; and 3) maximum hip flexion (MHF), defined as the maximum detected thigh angle for a given stride that occurs after MHE, triggers the transition to S3. These three gait events (HS, MHE, and MHF) are shared events across these primary locomotion tasks, but the corresponding gait phase and thigh angle at which these events occur changes based on the task (Fig. 1). Backwards progression through the state machine can also be considered when implementing in real-time, as in [38], but is not implemented in this work.

To be considered a phase variable that is unified across locomotion tasks, it is critical to ensure that the definition and structure of the phase variable $\phi$ remain the same for all tasks. Toward this, we define the unified piecewise phase variable to be

$$\phi = \begin{cases} \frac{\theta_{\text{th}}^{\text{HS}} - \theta_{\text{th}}}{\theta_{\text{th}}^{\text{HS}} - \hat{\theta}_{\text{th}}^{\text{MHE}}} \hat{\phi}^{\text{MHE}} & \text{if S1,} \\ \phi^{\text{MHE}} + \frac{\theta_{\text{th}} - \theta_{\text{th}}^{\text{MHE}}}{\hat{\theta}_{\text{th}}^{\text{MHF}} - \theta_{\text{th}}^{\text{MHE}}} (\hat{\phi}^{\text{MHF}} - \phi^{\text{MHE}}) & \text{if S2,} \\ \phi^{\text{MHF}} + \frac{\theta_{\text{th}}^{\text{MHF}} - \theta_{\text{th}}}{\theta_{\text{th}}^{\text{MHF}} - \hat{\theta}_{\text{th}}^{\text{HS}}} (1 - \phi^{\text{MHF}}) & \text{if S3,} \end{cases} \quad (1)$$

where $\theta_{\text{th}}^{\text{HS}}$, $\theta_{\text{th}}^{\text{MHE}}$, and $\theta_{\text{th}}^{\text{MHF}}$ are the measured thigh angle at the detected HS, MHE, and MHF, respectively, and $\phi^{\text{MHE}}$ and $\phi^{\text{MHF}}$ are the most recent estimated gait phase when MHE and MHF are detected (black in (1)). The model parameters $\hat{\theta}_{\text{th}}^{\text{MHE}}$ (blue), $\hat{\theta}_{\text{th}}^{\text{MHF}}$ (orange), and $\hat{\theta}_{\text{th}}^{\text{HS}}$ (green) are the predicted thigh angle for the upcoming MHE, MHF, and HS, respectively, and $\hat{\phi}^{\text{MHE}}$ (blue) and $\hat{\phi}^{\text{MHF}}$ (orange) are the predicted corresponding gait phases for the upcoming MHE and MHF. By definition, the predicted gait phase

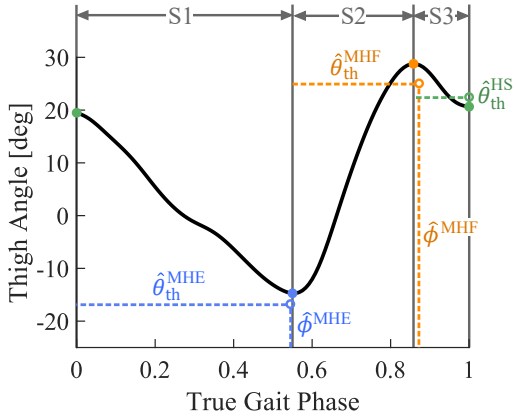


Fig. 2. The phase variable ($\phi$) is based on the sagittal plane thigh orientation ($\theta_{\text{th}}$). Three key gait events, MHE, MHF, and HS generally subdivide the gait cycle into an initial descending thigh angle state (S1), an ascending thigh angle state (S2), and a final descending state (S3). The unified piecewise phase variable transitions through these finite states by detecting HS, MHE, and MHF and seeks to accurately predict the thigh angle ($\hat{\theta}_{\text{th}}$) and the gait phase ($\hat{\phi}$) of the upcoming gait event (MHE is shown in blue, MHF in orange, and HS in green).

corresponding to the upcoming HS is a value of 1. An additional constraint exists on (1) such that if the phase variable $\phi$ is estimated to be greater than one or less than zero, it is saturated to stay within these bounds.

These 5 parameters ($\hat{\theta}_{\text{th}}^{\text{MHE}}$, $\hat{\theta}_{\text{th}}^{\text{MHF}}$, $\hat{\theta}_{\text{th}}^{\text{HS}}$, $\hat{\phi}^{\text{MHE}}$, and $\hat{\phi}^{\text{MHF}}$), representing predictions or initial guesses for the thigh angle and gait phase of the upcoming gait events (Fig. 2), collectively define the phase variable. Finding ways to accurately predict these upcoming gait features (referred to as the model parameters hereafter) is critical to ensuring a smooth, accurate, and monotonic phase variable progression. Two approaches for determining these model parameters are described below, first with task classification (Section II-B) and second without any knowledge of the locomotion task, but with contralateral-side sensor measurements (Section II-C).

### B. Phase Variable Unification With Classification

If we assume accurate and robust classification among a predefined set of locomotion tasks (an area that has received extensive research focus over the past decade [16], [17]), we may use the classified task to determine the appropriate model parameters to employ. Fig. 3 shows that a relationship exists between the ground inclination (spanning stairs, ramps, and level ground) and the five model parameters. By classifying the locomotion task, these relationships can be used as a lookup table to generate the predictions for the upcoming gait features. In this work, the models for $\hat{\theta}_{\text{th}}^{\text{MHE}}$, $\hat{\theta}_{\text{th}}^{\text{MHF}}$, $\hat{\phi}^{\text{MHE}}$, and $\hat{\phi}^{\text{MHF}}$ are given in Figs. 3a, 3b, 3d, and 3e, respectively and are used directly for the tasks represented in the dataset. Unlike the other parameters, the final predicted parameter $\hat{\theta}_{\text{th}}^{\text{HS}}$ (Fig. 3c) is based on the most recently measured thigh angle at MHF ($\theta_{\text{th}}^{\text{MHF}}$) and the expected change in thigh angle between MHF and HS. This was also explored for other parameters, but only offered benefit when predicting $\hat{\theta}_{\text{th}}^{\text{HS}}$ due to the relatively small change in thigh angle between MHF and HS. Training for these parameter models is described further in Section II-D.

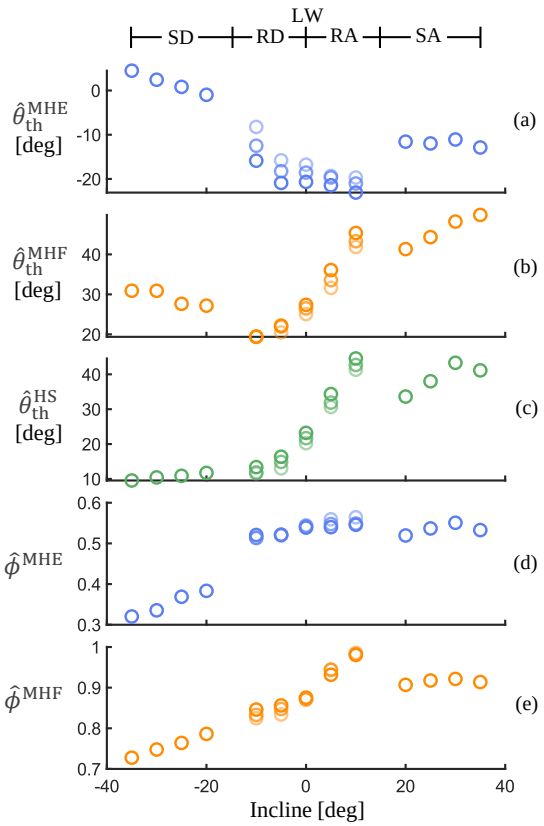


Fig. 3. Using classification, predictions for the expected thigh angle ($\hat{\theta}_{th}$) and gait phase ($\hat{\phi}$) at MHE, MHF, and HS can be generated based on the classified locomotion task. For walking tasks, speeds include 0.8 (more transparent), 1.0 (less transparent), and 1.2 m/s (no color transparency).

While this model is well suited for control frameworks that have high-fidelity task classification, this dependence could potentially be limiting. Using more continuous estimates of speed or ground slope could reduce the classification demands and improve the overall performance [19], but the dependence on classification for this phase variable approach may still be undesirable. Therefore, we also propose a second approach for a unified phase variable definition that is completely task-agnostic in Section II-C.

### C. Task-Agnostic Phase Variable Unification

An alternative way to generate predictions for the upcoming gait event parameters is to use bilateral sensing. Figure 3 from the previous model shows that, without classification, the model parameters based only on the prosthesis-side thigh orientation would be redundant across some tasks. For example, there is not enough information contained in the unilateral thigh orientation to distinguish between stair-ascent and −10-degree ramp descent when predicting $\hat{\theta}_{\text{th}}^{\text{MHE}}$ (Fig. 3a) or $\hat{\phi}^{\text{MHE}}$ (Fig. 3d). By measuring the global thigh orientation in the sagittal plane from *both* the prosthesis-side and intact-side legs, sufficient information can be obtained to predict the thigh orientation and timing of the next gait event. In particular, the bilateral thigh orientations of the

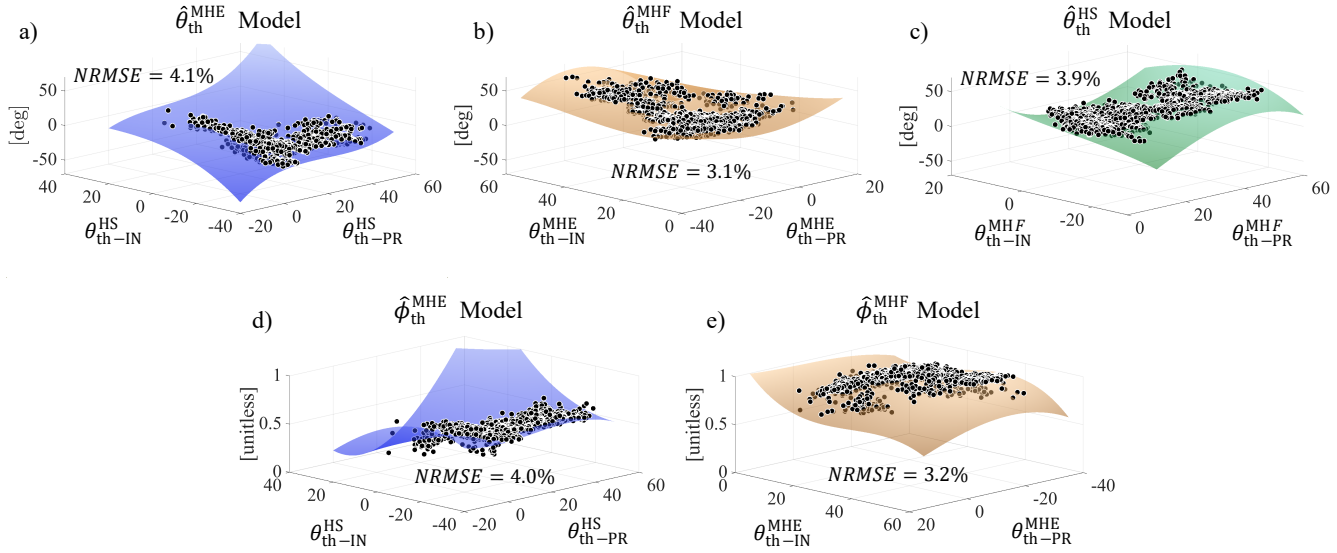


Fig. 4. Without any knowledge of the locomotion task, models spanning several activities can be generated to predict the upcoming gait event information based on bilateral thigh angle information at the time of the previous gait event. The measured thigh angle on the prosthesis-side leg at the moment of prosthesis-side HS ($\theta_{\text{th-PR}}^{\text{HS}}$) and the measured thigh angle on the intact-side leg at the moment of prosthesis-side HS ($\theta_{\text{th-IN}}^{\text{HS}}$) can be used to predict a) the upcoming prosthesis-side thigh angle at the upcoming MHE ($\hat{\theta}_{\text{th}}^{\text{MHE}}$) and d) the corresponding gait phase ($\hat{\phi}^{\text{MHE}}$). Likewise, measured bilateral thigh angles at the moment of prosthesis-side MHE can be used to predict prosthesis-side MHF thigh angle (b) and gait phase (e). Measured thigh angles at prosthesis-side MHF can predict $\hat{\theta}_{\text{th-PR}}^{\text{HS}}$, and the gait phase of the upcoming HS is always 1. All horizontal axes are in units of degrees.

current gait event can be used to define a continuous model for the upcoming gait event, as shown in Fig. 4.

For example, Fig. 4a uses the measured thigh orientation from both legs at the moment of prosthesis-side HS to predict the orientation of the prosthesis-side thigh at MHE. Each parameter is modeled as a cubic surface, taking the form

$$\begin{aligned}\hat{X} = p_{00} + p_{10}x + p_{01}y + p_{20}x^2 + p_{11}xy \\ +p_{02}y^2 + p_{30}x^3 + p_{21}x^2y + p_{12}xy^2 + p_{03}y^3,\end{aligned} \tag{2}$$

where $\hat{X}$ is the model parameter corresponding to the predicted upcoming gait feature, $x$ is the prosthesis-side thigh angle measured at the most recent prosthesis-side gait event, and $y$ is the intact-side thigh angle measured at the same instant. In Fig. 4d, for example, $x = \theta_{\text{th-PR}}^{\text{HS}}$ and $y = \theta_{\text{th-IN}}^{\text{HS}}$ are used as inputs to predict $\hat{X} = \hat{\phi}^{\text{MHE}}$, the predicted gait phase at the upcoming prosthesis-side MHE. The polynomial coefficients are fit by minimizing the L2-norm of the difference between the predicted and actual signals (e.g., $\hat{\phi}^{\text{MHE}}$ and $\phi^{\text{MHE}}$) from the training data (details in Section II-D). The normalized root-mean-squared error (NRMSE) performance for each model is given in Fig. 4 as a percentage of the signal range (100 deg for thigh angle parameters and 1 for phase parameters), showing good predictive performance for each model.

### D. Data Processing

Both the classification-dependent model (Section II-B) and the task-agnostic model (Section II-C) were assessed using an able-bodied open access dataset consisting of 10 able-bodied individuals completing several tasks [37]. To train both the classification-dependent and task-agnostic models, the data from five of the subjects in [37] were used, and the remaining five subjects were used for validation. Tasks of LW at 0.8, 1.0, and 1.2 m/s speeds, RA and RD at 5 and 10 degrees using the same 3 speeds, and SA and SD at inclines of 20, 25, 30, and 35 degrees at a self-selected pace were used for training and validation. Walking was more represented in the training data than stair climbing, so relative weights were added to the optimization cost to balance the contribution from each task equally. Thigh angles were calculated as the sum of the negative global pelvis angle from vertical and the positive hip angle, both in the sagittal plane, such that a positive/negative thigh orientation corresponds to hip flexion/extension. Heel strike was provided by the dataset and the ground-truth gait phase was defined as the normalized time between consecutive heel strikes. MHE was determined for all strides as the moment between HS events at which thigh angle was minimized, and MHF was determined as the first maximum peak in thigh angle that occurred between MHE and the upcoming HS (a single peak existed in 88.4% of strides in all activities, with 6.8% having no peaks and 4.8% having 2 peaks).

Only steady-state strides were used for all activities. For walking tasks, the right leg was treated as the prosthesis-side, but for stair trials the prosthesis-side was selected as the leading foot to ensure that there were two HS events in steady state on the 4-step staircase [37]. For the task-agnostic model that uses bilateral thigh information, the intact-side thigh information was taken from the continuous streaming dataset, which contained bilateral sensing. Strides exhibiting erroneous discrete jumping behavior in the dataset were removed (6 total out of 4,215), but no outliers were removed otherwise. The classification-dependent gait event prediction models (Fig. 3) were generated by taking the average thigh angle and gait phase for each gait event of HS, MHE, and MHF. For validation, phase prediction error

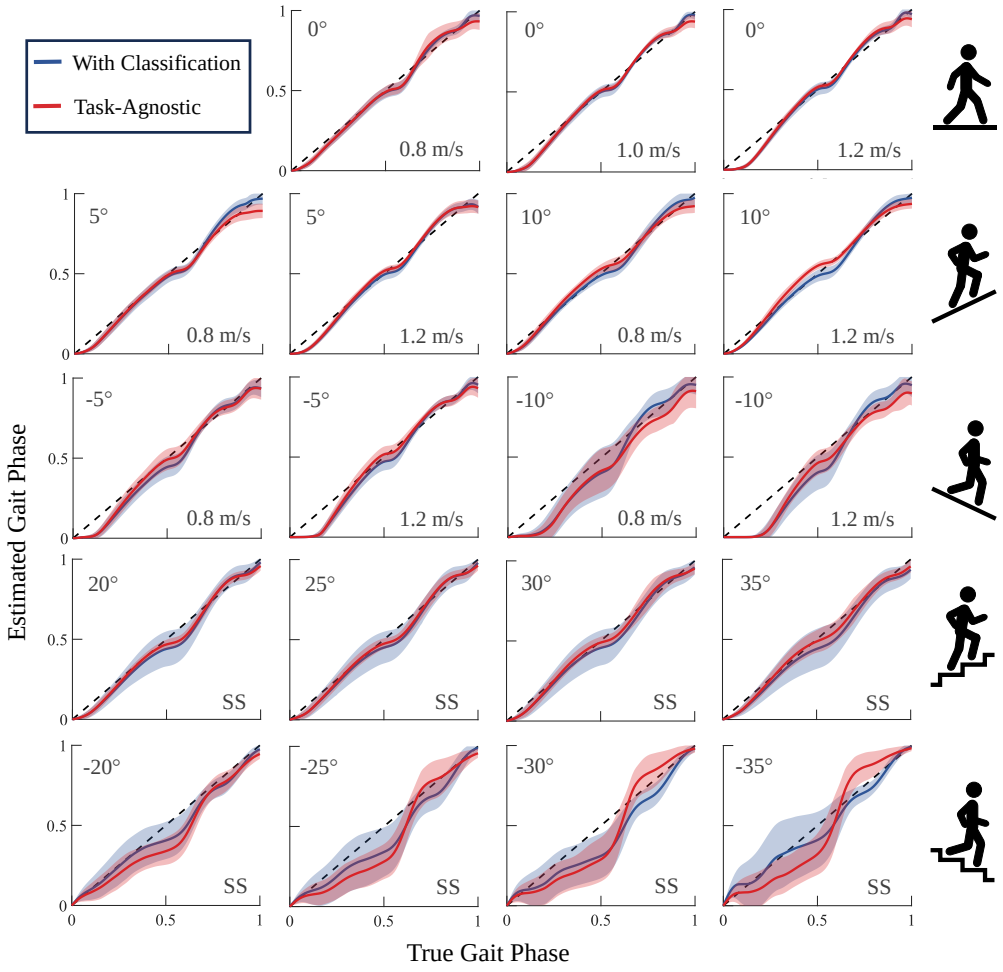


Fig. 5. The average gait phase estimation ± one standard deviation is compared to the true time-normalized gait phase (dashed grey). For each locomotion activity, the task incline is displayed in the top left corner, and the task speed in the bottom right corner (SS indicating self-selected). Averaged across subjects, the unified phase model with classification (blue) and without knowledge of the task (red) exhibit comparable prediction performance across tasks, with the task-agnostic approach having less subject-to-subject variability.

was quantified for each stride by taking the root-mean-squared error (RMSE) between the ground-truth gait phase and the model predicted gait phase. Differences between the classification-dependent and task-agnostic phase models were compared using a two-tailed paired t-test.

## III. Results and Discussion

### A. Simulation Results

The overall phase estimation performance across multiple ADLs and speeds is shown in Fig. 5 both with classification and without classification (task-agnostic). Across all tasks, subjects, and strides, the overall average RMS phase error for this unified phase approach was 6.8% with classification and 6.3% when task-agnostic. The corresponding average RMS phase error is summarized for individual tasks in Fig. 6. For level walking (LW), the phase estimation is very consistent both with and without the use of classification, with an average phase RMSE between 4-5% for both conditions at all three speeds. This consistency is maintained for ramp ascent tasks, where both models have RMS error less than 5% on average for all speeds and ramp inclinations.

For stair ascent (SA), the task-agnostic approach demonstrated higher accuracy (phase RMSE of 4.9% across stair heights) than the classification-dependent model (phase RMSE of 8.1%) with statistical significance ($p = 4.0 \times 10^{-17}$). The SA phase estimation with classification exhibited higher subject variability, performing better for some subjects (such as AB05: average phase RMSE 5.8% for 35 deg SA) than for others (AB09: 8.6%). SA phase estimation was more consistent across subjects using the task-agnostic model (AB05: 4.4%, AB09: 4.8%, for the same trials). The task-agnostic phase model's better accommodation of subject variability over the approach with classification is also observed in the reduced standard deviation throughout Fig. 5. This is likely due to the incorporation of more recent gait event information in the task-agnostic predictions.

During 5-degree ramp descent, the unified phase approaches maintained repeatability across strides and subjects (low standard deviation in Fig. 5) and an average phase RMSE less than 7.2% with classification and 6.6% with the task-agnostic framework. Phase estimation error increased for the steeper ramp descent of 10 degrees, with an average

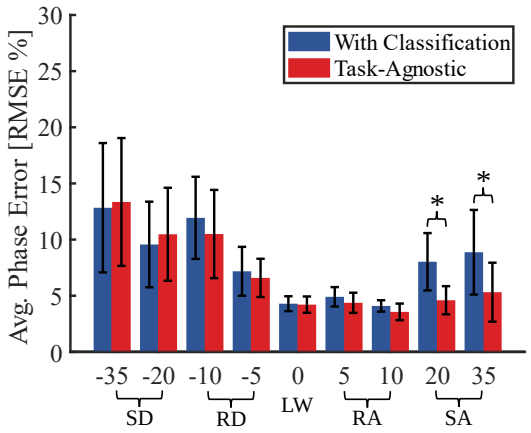


Fig. 6. The average phase root-mean-squared error (RMSE) ± one standard deviation for each locomotion task is measured as a percentage. The task-agnostic approach (red) performed consistently during level walking and all ascent tasks, with increased error for descent tasks. The classification-dependent approach (blue) behaved similarly, but with significantly larger error during stair ascent (SA) across stair heights ($p = 4.0 \times 10^{-17}$).

phase RMSE less than 12% with classification and less than 11% with task agnosticism. Fig. 5 reveals that a significant error exists in the early stance phase (weight acceptance) for ramp descent and generally becomes larger with increased speed and more significant ground inclination. In this region, the phase tends to saturate at zero, meaning that the thigh angle begins to flex after heel strike rather than to approach the predicted MHE value for these tasks. This behavior is consistent with early stance weight acceptance, which is generally increased with higher walking speeds and steeper declines. This early stance error (exhibited in [8] and [9] as well) can also be observed to a lesser degree for LW, with the largest early stance errors presented at 1.2 m/s. Future work could consider an additional optional state to the FSM that could accommodate this early hip flexion for some tasks, although this would introduce increased sensing and modeling demands that could be difficult in practice.

Among all locomotion tasks, stair descent (SD) consistently showed the poorest model performance, with mean phase RMSEs of 12.1% (with classification) and 12.7% (without), particularly at larger stair heights (Fig. 6). The causes of reduced accuracy, however, seemed to differ between the two approaches. In this framework, poor phase estimation generally reflects discrepancies between predicted parameters $\hat{\theta}_{\text{th}}^{\text{MHE}}$, $\hat{\theta}_{\text{th}}^{\text{MHF}}$, $\hat{\theta}_{\text{th}}^{\text{HS}}$, $\hat{\phi}^{\text{MHE}}$, and $\hat{\phi}^{\text{MHF}}$ and their ground-truth values. Figure 7 shows that with classification, SD phase predictions varied across subjects, with better accuracy for some (e.g., AB09) and worse for others (e.g., AB07), occasionally resulting in phase over- or underestimates. The task-agnostic approach, however, consistently underestimated gait phase at MHE and thigh angle at MHF, creating an S-shaped phase curve across subjects. While the task-agnostic model was generally more consistent, its large phase RMS errors for SD reflect optimization trade-offs that prioritize balanced performance across all activities over individual task accuracy.

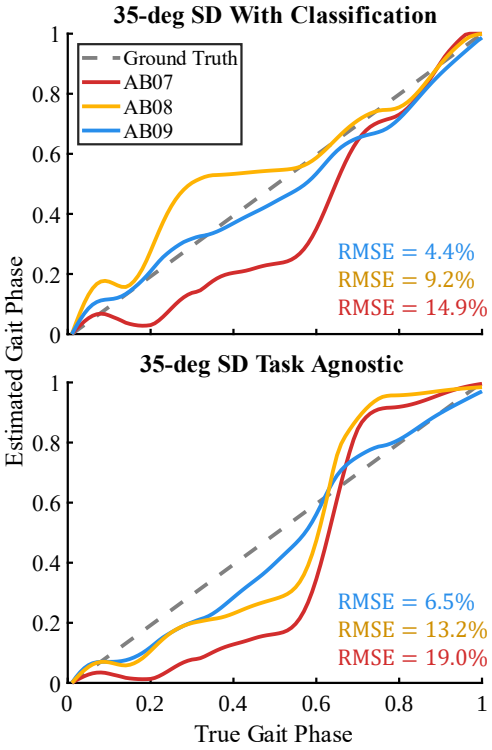


Fig. 7. Both the classification-dependent (top) and task-agnostic (bottom) approaches had the highest phase prediction error during 35-degree stair descent (SD). These models performed better for some subjects (e.g., AB09, blue) and worse for others (e.g., AB07, red).

### *B. Comparison with Other Multi-Activity Phase Estimators*

This work is inspired by the phase definitions in [8], [9], [38] that accommodate variable slope/speed walking, variable-height stair climbing, and obstacle avoidance, respectively; however, the unified phase definition presented herein is the first to unify these definitions into a single framework. Continuous gait phase monitoring across multiple ADLs without classification dependence has also been explored in [18] for prostheses and [30], [36], [40] for exoskeletons. For example, [18] used bilateral sensing to simultaneously predict gait phase and task for a robotic ankle prosthesis, achieving average phase errors under 2% for walking and under 4% for stairs. Similarly, [30] used bilateral sensing and a random forest regression algorithm to estimate gait phase and classify tasks for a soft exosuit, showing effective phase prediction for walking and stairs, with a nearly three-fold error increase during SD compared to LW. Using bilateral sensing and deep neural networks, [36] achieved an overall phase RMSE of 5.04% for exoskeleton control across ten subjects, with errors increasing by 50% during RD compared to LW. RMSE errors reached nearly 10% during SD, similar to the trends observed in this study. With very steep slope walking, [40] also used bilateral sensing to achieve an average phase RMSE of 4.8%, and exhibited large subject dependence in performance.

Each of these approaches used bilateral sensing to obtain a task-agnostic phase estimate, and the present work is the first to do so towards transfemoral prostheses. The related

work and our approaches herein saw a notable decrease in performance during stair descent, which could be due to the relatively small range of motion of the hip that causes sensitivity between the angle of the user's thigh and the gait phase, as proposed in [9]. Unlike [30], [36], this unified phase definition is a model-based approach that does not incorporate ML. The imposed model structure based on common kinematics observed across tasks (Fig. 1) could also be used to enhance ML approaches that could learn the structured model parameters, rather than to learn the full mapping from lower-limb kinematics to gait phase. This could aid in prediction robustness when encountering out-of-training inputs, such as new speeds and inclines. Our approach to unified phase also depends only on bilateral thigh sensing (omitting any trunk, shank, or foot sensors as found in [18], [30], [36], [40]), which holds significant promise for the control of transfemoral prostheses.

### C. Challenges for Real-Time Implementation

The analysis presented in this work detected HS, MHE, and MHF offline. In practice, heel strike (or foot strike) information is relatively simple to obtain in real-time, but it can be more difficult to accurately detect MHE and MHF without delay. Fast real-time detection algorithms have been developed to detect peaks in the thigh angle associated with MHE and MHF from a single thigh IMU based on thresholding [38] and multiple moving average algorithms [9]. Appropriate performance of this unified phase definition depends on this real-time detection.

Furthermore, the use of bilateral sensing (as in this work and [18], [30], [36], [40]) increases donning requirements, especially for the use of unilateral prosthetic control, which is undesirable from the perspective of clinical and commercial adoption. If it can be shown, however, that performance or robustness to latent variability could be dramatically increased with the incorporation of additional sensors (such as a single additional IMU on the contralateral limb in this case), the benefits may justify the perceived drawbacks. In this work, we preliminarily suggest that a task-agnostic framework for continuously estimating phase across locomotion tasks may not be feasible with a single thigh IMU, but that it can be done with a pair of bilateral thigh IMUs. While both approaches showed similarly good performance, breaking the dependence on classification is a significant advantage as classification between many activities is challenging and fundamentally unscalable.

### D. Limitations and Future Work

While the unified and task-agnostic approach presented has shown promise when simulated offline, future work will seek to validate these results in real-time hardware experimentation. It will be important to ensure the robustness of this approach when transitioning to real environments, accounting for the sensor challenges as discussed, and implementing this with the target population of individuals with unilateral transfemoral amputation.

The primary performance limitation presented for both the classification and task-agnostic approaches is that subject variability was high, leading to good performance for some subjects and worse for others. Personalization of these phase prediction models could lead to significant improvement in performance. While it is undesirable to increase tuning demands, which would require extensive clinician time and training, this approach is an ideal candidate for personalizing to a specific user over time, with techniques such as the Kalman filter (as in [40]). After the gait event information for MHE, MHF, and HS is predicted by the model, the corresponding ground-truth information is then measured for each stride. Comparing the predicted and ground-truth values could be used to improve the model for an individual user over time, which could also reduce the effects of latent variability. Future work will pursue such personalization techniques that do not increase tuning demands.

## IV. Conclusion

In this study, we presented a novel unified phase variable framework for robotic lower-limb prostheses, enabling both classification-based and task-agnostic control across a diverse range of locomotion tasks. By unifying phase definitions across level walking, ramp ascent/descent, and stair ascent/descent with several speeds and inclines, this approach addresses limitations of existing methods that are classification-reliant and employ activity-specific phase definitions. Simulation results demonstrated that both classification-based and task-agnostic implementations achieve low phase RMSE, with the task-agnostic approach exhibiting reduced subject-specific variability. The task-agnostic model also outperformed the classification-based model during stair ascent, which highlights its robustness across diverse activities and may justify the use of bilateral sensing. These findings highlight the feasibility of using task-agnostic frameworks in the development of robust and versatile prosthetic control systems that can accommodate a wide range of locomotion tasks.

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