PACE: Perception-Aware Contact Estimation and Slip Detection through Dynamic Map Analysis

***Abstract*— Accurate contact estimation is essential for reliable legged locomotion on challenging terrains, yet existing methods often assume stable footholds and fail under slip, which is particularly common when climbing stairs. In this work, we present Perception-Aware Contact Estimation (PACE), a probabilistic framework that fuses proprioceptive slip cues with exteroceptive terrain data to dynamically adjust contact confidence. PACE extends prior fusion approaches by incorporating velocity discrepancies and elevation map analysis, enabling earlier and more robust slip detection on discontinuous surfaces. We validate PACE on a Unitree Go1 climbing an oil-coated step designed to induce slips. Experiments reveal that, while a baseline method misclassifies all slips as firm contact, PACE reduces gross misclassifications and provides more robust estimates, particularly during larger slips. These results demonstrate that terrain-aware fusion improves contact reasoning in conditions where conventional methods fail.**

I. Introduction

Legged robots offer significant advantages over wheeled counterparts when navigating complex, real-world terrains. Their ability to overcome discontinuous elevation changes, such as stairs, is a key differentiator, enabling mobility in environments inaccessible to traditional wheeled platforms. Substantial research efforts have advanced the perception and control capabilities required to map terrain, localize the robot, and compute control inputs that drive the robot toward its goal [1]–[4].

Despite these advances, real-world performance remains limited by noisy exteroceptive sensors, communication delays, and dynamic environmental changes. These factors often manifest as small but critical deviations in when and where the a robot's end effectors (i.e. feet) make contact with the terrain. Since locomotion stability fundamentally depends on the timing, location, and quality of end effector contacts, errors in contact estimation can propagate through state estimation and control. Whole-Body Controllers (WBCs) commonly assume that end effectors are stationary during contact and capable of fully applying the planned forces [5]. Likewise, state estimation methods based on leg kinematics, such as [6], presume that changes in end-effector height in the body frame during contact correspond directly to changes in body height in the world frame. Deviations from these assumptions, caused by incorrectly timed contacts or slipping, can lead to substantial discrepancies between estimated and actual state, ultimately degrading control performance and increasing the risk of falls.

These challenges are particularly acute when traversing terrain with discontinuous elevation changes, precisely the kind of environments where legged robots outperform wheeled systems. In such settings, even brief slips can invalidate assumptions made by the state estimation and control systems, and introduce large state discrepancies, by slipping off of a stair for example. Detecting slip is therefore critical for maintaining stability and preventing falls. While some prior work has addressed slip detection specifically, these efforts often focus on flat, low-friction environments and remain insufficient for reliably handling stairs and other abrupt terrain transitions.

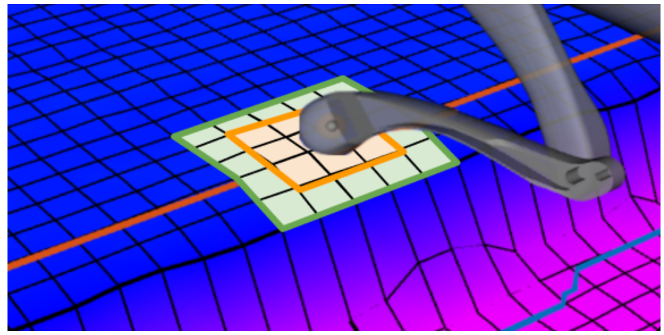

Fig. 1: Cell weighting based on distance from contact point.

Several proprioceptive methods have been proposed for detecting slip events in legged locomotion. Focchi et al. [7] present a velocity-based approach that compares end-effector velocity to body velocity. Significant discrepancies between the two are used to estimate the surface normal, coefficient of friction, and to trigger slip recovery. Nisticò et al. [8] refine this technique by computing end-effector velocity in the body frame rather than the world frame and by quantifying slip significance based on the distance traveled during the slip event. Notably, both approaches are most effective at detecting slip after contact has already occurred; they are not designed to detect early or premature contact.

Manuelli and Tedrake [9] employ a momentum observer to implement an optimization-based particle filter that localizes the contact point on the robot. While accurate, this method incurs high computational cost, averaging 161 ms per contact localization, making it impractical for time-sensitive tasks such as stair climbing, where contacts are brief and frequent. Moreover, since stair contacts are limited to the feet, full-body contact localization is unnecessary.

Teng et al. [10] introduce an Invariant Extended Kalman Filter that fuses leg kinematics with visual input to estimate state in slippery environments. However, while effective in low-friction scenarios, this method is susceptible to drift and has not been validated in terrains with abrupt elevation changes, such as stairs.

Manuscript 5086 submitted to 2026 IEEE International Conference on Robotics and Automation (ICRA). Received September 15, 2025.

Jenelten et al. [11] propose a probabilistic contact model that incorporates kinematics, dynamics, and differential kinematics within a Hidden Markov Model to detect slips. One limitation is that contact must already be registered for slip to be inferred. Their control strategy involves joint stiffening and assumes uniform terrain characteristics across all legs and over time—an assumption that does not hold on staircases. Furthermore, the approach is predominantly proprioception-centric and developed for flat terrain.

Maravgakis et al. [12] present a method for contact detection based solely on inertial measurements, using a kernel density estimator. While well-suited for robots with limited sensing, the reliance on IMUs introduces vulnerability to drift and noise, especially compared to fused sensor estimates.

Bledt et al. [13] use an instantaneous Kalman filter variant to fuse foot height, proprioceptive force estimates, and gait timing in order to infer contact probabilities. However, their approach omits vision and terrain data, reducing its applicability in perceptive locomotion tasks.

In addition to proprioception, some researchers have focused on the foot design and sensing to improve slip detection. For example, Okatani and Shimoyama [14] developed a MEMS-based local slip sensor that evaluates ground slipperiness during foot impact to improve slip prediction at contact onset. The sensor integrates a piezoresistive elastomer with a curved surface and shock absorber, enabling it to detect local slip through deformation immediately after contact. It successfully distinguished slipperiness in dynamic conditions, but was ultimately only evaluated on flat, uniform ground.

While effective within their intended scope, particularly for detecting and managing slips on flat, low-friction, and static terrains, the aforementioned methods are not designed or evaluated for one of the most common and challenging obstacles in legged locomotion: stairs. The large, discrete elevation changes characteristic of stairs introduce unique dynamics that existing contact estimation frameworks fail to address.

In this work, we introduce a novel slip detection framework: Perception-Aware Contact Estimation (PACE), which leverages exteroceptive terrain data to dynamically update contact confidence, providing more accurate contact estimates. Specifically, we integrate terrain and kinematic uncertainty into the contact belief update. PACE leverages grid-based terrain analysis to identify abrupt elevation transitions and dynamically update contact confidence based on terrain features. To this end, we build on the sensor fusion approach of [13], and extend it by incorporating additional velocity-based slip detection metrics from [7], resulting in a more comprehensive and robust perception-aware estimation of contact state. Our core contributions include the following:

- We introduce PACE, probabilistic method that fuses proprioceptive slip cues with terrain data for perception-aware contact estimation.
- We extend prior work by integrating velocity, force deviations, and elevation map analysis for early slip detection.

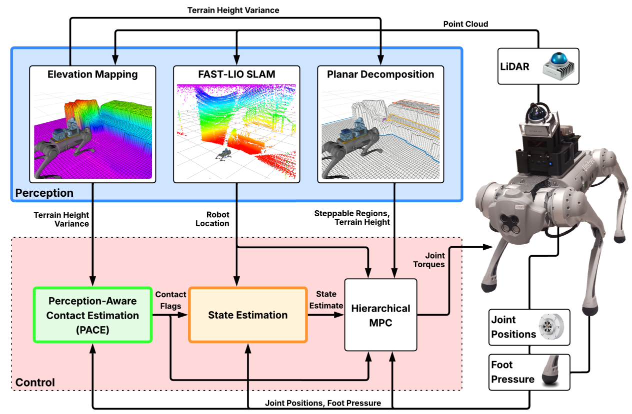

Fig. 2: System Pipeline modified from [15] with PACE added

- We validate PACE on slippery steps, demonstrating robust slip detection on a Unitree Go1, and reducing misclassifications versus baseline methods.

The remainder of this paper is organized as follows. Section II introduces our methodology, including probabilistic contact model fusion, elevation mapping, and map analysis. Section III describes the experimental setup and presents and discusses the corresponding results. Finally, the paper is concluded in Section IV.

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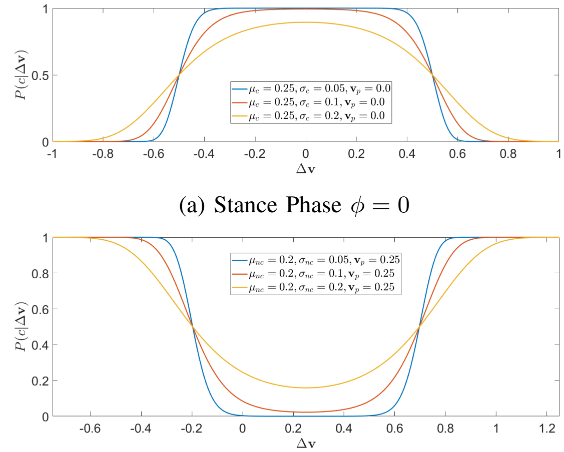

(a) Stance Phase $\phi = 0$

(b) Swing Phase $\phi = 1$

Fig. 3: Probability of Contact vs Difference Between Desired and Measured Foot Velocity.

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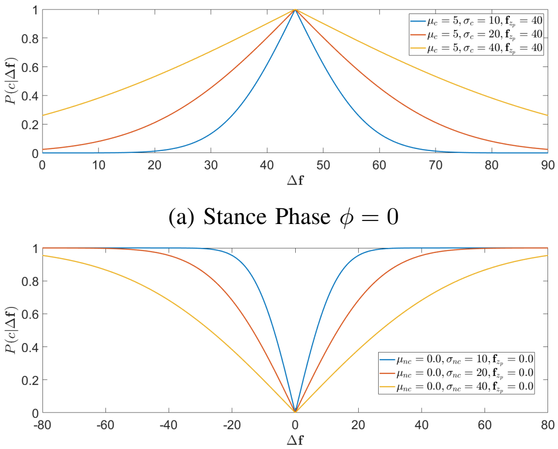

(a) Stance Phase $\phi = 0$

(b) Swing Phase $\phi = 1$

Fig. 4: Probability of Contact vs Difference Between Desired and Measured Force.

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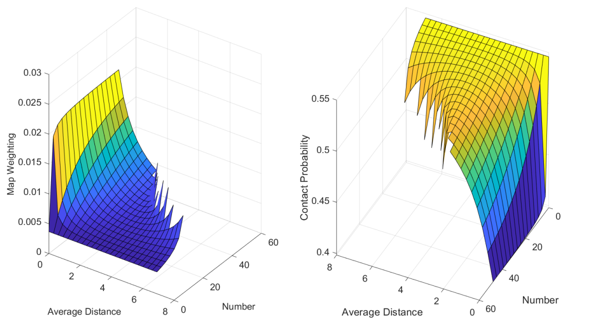

Fig. 5: Probability of Contact and Map Weighting Given Average Distance and Average Number of Squares with a 10 cm Difference in height.

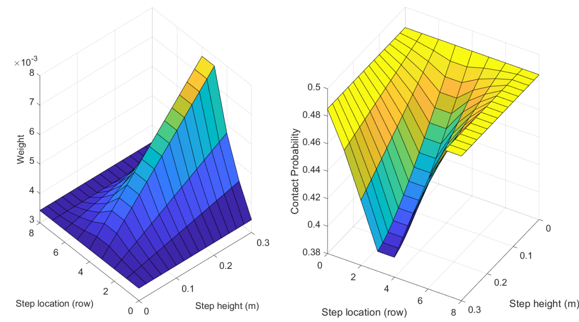

Fig. 6: Probability of Contact and Map Weighting Given Number of Rows in a Step and the Height of a Step.

Fig. 7: Experimental setup showing a slip from stepping on an oily surface. Consecutive video frames are overlaid to highlight the small slip. A computer in the background shows the time to allow syncing up video and rosbag data.

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III. Experimentation and Results

A. Experimental Setup

To evaluate our approach, we conducted a series of experiments by commanding the robot to step onto an elevated platform with a sloped edge coated in oil, while recording the robot's internal representation of its contact estimation alongside video data. This setup can be seen in Fig. 7 demonstrating the foot in contact slipping downward on the sloped edge. The sloped edge and reduced coefficient of friction encourage slipping, while the elevation provides a realistic approximation of a stair. The change in height of the sloped edge is below a threshold that allows the slope to be integrated into the plane beneath it, effectively making it invisible to the robot. This setup is both repeatable and allows the vision system to accurately capture elevation changes. The experiments were performed using a Unitree Go1 quadruped robot, equipped with a Livox Mid360 LiDAR sensor. Computation was handled onboard using an Intel NUC i7 11$^{\text{th}}$ gen.

By evaluating the internal data against the video data we can qualitatively determine when the robot is slipping. Sometimes a foot will shift a few millimeters on contact before settling, making the line between slips and non-slips blurry. For this reason we focus on analyzing large slips, greater in distance than 3 cm, and where the foot is in motion for a majority of the contact time. While Fig. 7 shows a small slip (less than 3 cm), Fig. 8 shows a large slip. In what follows, we compare how the baseline control [13] and PACE methods react to the slip.

To evaluate performance, we compare the estimated body position using a traditional static contact estimation approach against our proposed dynamic contact estimation. The full system pipeline used in these experiments is taken from [15] and is illustrated in Fig. 2.

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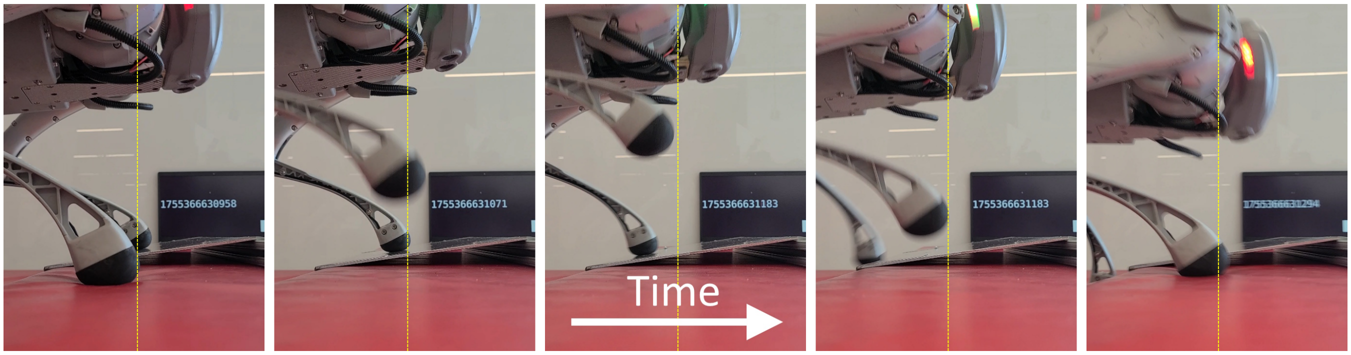

Fig. 8: Video frames show the front left leg experiencing a large slip. Robot places its left foot onto the slippery platform and the foot slides off over the course of 336 ms. A yellow line marks location of initial contact.

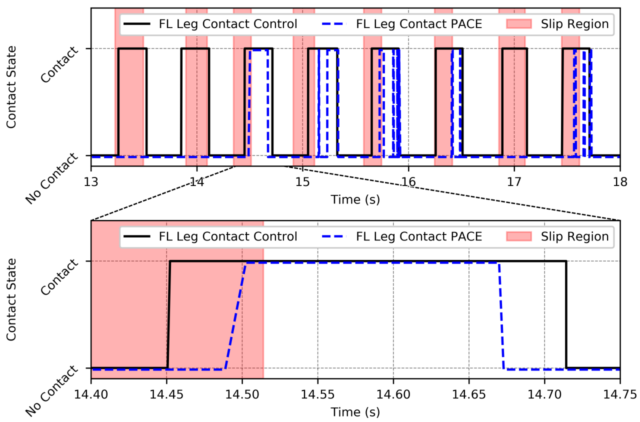

Fig. 9: Front Left Leg Control Estimate in Slippery Conditions vs Estimate with Map Analysis. Two plots show multiple slips (top), as well as one slip in greater detail (bottom).

B. Results

We evaluated our method against a standard contact estimator without velocity modeling as in [13] on the slippery step-up experiment described in the previous section. Figure 9 illustrates the difference between the two approaches for a single-leg contact during slip events. The baseline control method consistently misclassified slips as firm contact. In all observed large-slip trials, the control estimator failed to detect loss of contact, incorrectly reporting 7/7 large slips as stable contact. This behavior is expected given its reliance on static assumptions about foot height and force measurements, both of which are unreliable when the foot is sliding along an inclined surface or slipping onto a lower one. By contrast, our method demonstrated improved performance, with *all* observed slips off a stair detected for the duration of their slip off the stairs. This represents a 100% success rate for large slips (larger than 3 cm). Our method also detected 25% of the smaller slips that remained on the stairs. Slips that went undetected and were instead classified as contact typically corresponded to low measured foot velocities. Across detected slips, the average foot velocity was 0.132 m/s, with

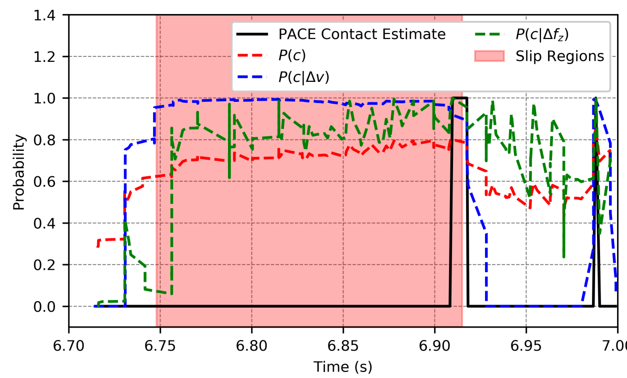

Fig. 10: Force and Velocity Contributions to Slip Detection with a False Positive Due to *Force*.

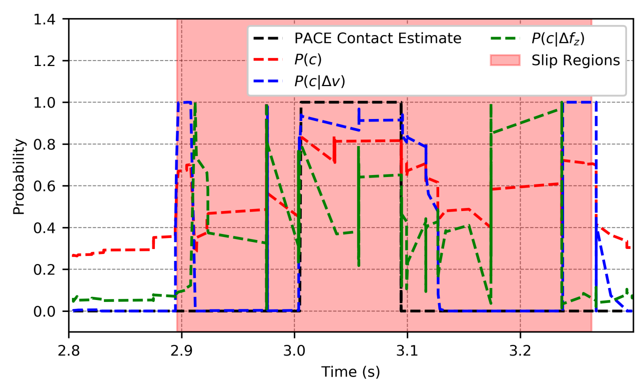

Fig. 11: Force and Velocity Contributions to Slip Detection with a False Positive Due to *Velocity*.

the lowest detected velocity being 0.067 m/s. Meanwhile, for false negatives the average velocity was 0.060m/s.

Figures 10 and 11 show cases where PACE misclassifies slips as contact. In the figures, $P(c)$ shows the non-thresholded probability of contact, $P(c|\Delta v)$ and $P(c|\Delta f_z)$ show the contribution of velocity and end effector z force to the contact probability respectively, and *Contact Estimate* shows the final output of PACE. Figure 10 shows a brief misclassification of a slip condition as contact due to noisy force sensor readings

TABLE I: False Positive and Negative Rate Compared to Measuring Velocity Alone as [7].

	FP Rate	FN Rate	Misclassification Rate
$\lvert\dot{x}_b\rvert = 0.01$	0.276	0.001	0.277
$\lvert\dot{x}_b\rvert = 0.05$	0.170	0.029	0.199
$\lvert\dot{x}_b\rvert = 0.1$	0.102	0.043	0.145
PACE	0.040	0.062	0.102

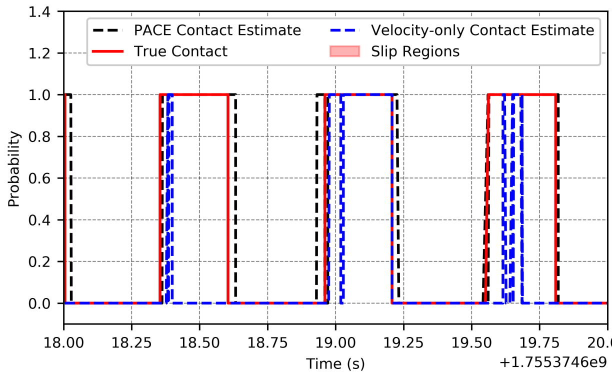

Fig. 12: Probabilistic Slip Detection vs Velocity Only Slip Detection on Flat Ground. Note that there are no slips in this figure.

TABLE II: False Positive Rate When Far From the Stair.

	FP Rate
$\lvert\dot{x}_b\rvert = 0.01$	0.296
$\lvert\dot{x}_b\rvert = 0.05$	0.171
$\lvert\dot{x}_b\rvert = 0.1$	0.101
PACE	0.024

at $t = 6.91$. Figure 11 shows a similar situation but caused by velocity measurements at $t = 3.0$. In this case we believe the false reading is caused by the foot slowing down when it switches directions (from sliding forwards to backwards). This explains the brief duration of the reading, from $t = 3$ to $t = 3.1$, as the foot moves too slowly to register as a slip.

Compared to [7], our approach reduces the number of false slip detections when the foot is in stable contact, while maintaining a comparable overall slip detection rate. TABLE I reports the total number of incorrect classifications at several cutoff foot velocities (0.1, 0.05, 0.01 m/s), alongside the results from our method. Notably, our method has the lowest overall misclassification rate and a 39% lower false positive rate compared to the velocity-based method. This is because our probabilistic method includes force-based features which, as shown in Fig. 12, makes our approach less susceptible to false positives.

We further validate that our map-based weighting of probabilistic inputs reduces the likelihood of false positives. TABLE II reports the false positive rate when the robot operates away from the stair region. Our method achieves a substantially lower rate than the baselines, as the map correctly identifies these areas as low-risk for slips. Supporting this interpretation, the results in TABLE II correspond to an average map value of $\epsilon = 0.0308$ while the results in TABLE I correspond to an average value $\epsilon = 0.1280$.

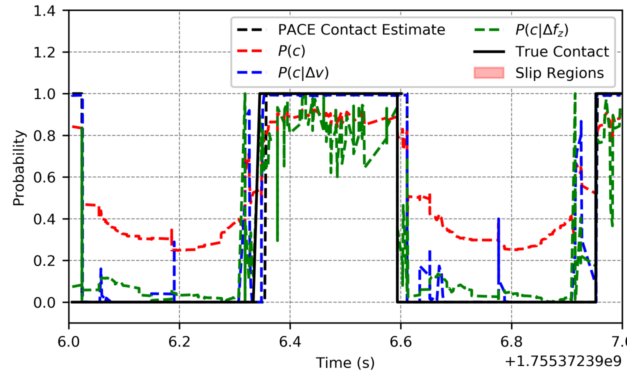

Fig. 13: Velocity and Force Contributions to Contact Detection with no Slips.

We observe, then, that the false positive rate when far from discrete changes in elevation is 40% of the false positive rate when near the stairs. Clearly, our map weighting plays a significant role in minimizing our false positive rate.

When slips were detected, our method responded quickly to the sharp changes in foot velocity and contact force that characterize slip events. For slips that began or ended partway through a contact, the estimator identified slip cessation on average 18 ms before the foot was visually observed to stop moving. Similarly, slips that began mid-contact were detected on average 32 ms after the onset of motion. Overall, these results indicate that our method achieves faster and more reliable slip recovery than the baseline control approach.

The presented results indicate that while neither method perfectly resolves the ambiguity of minor slips, PACE maintains improved accuracy over the control while offering a principled framework for incorporating terrain awareness, contact detection, and proprioceptive slip cues. The observed differences support the claim that perception-aware filtering is a viable pathway toward more robust contact estimation in discontinuous environments.

In addition to the ability to detect slips, an added benefit of our method is its ability to detect contact rather than relying on an external contact detector to detect slips on. To this end, we have leveraged foot velocity in a manner that benefits our contact detection. Figure 13 demonstrates how both force and velocity cause the overall probability of contact to overcome the threshold. Both force and velocity appear to recognize the same jump into high probability of contact before the contact is actually determined to be made. This is because the foot often hits the stair and bounces off, which our method accurately rejects as contact.

IV. Conclusions

This paper presented PACE, Perception-Aware Contact Estimation, as a novel method for adapting contact estimation using terrain information to produce a probabilistic slip and contact estimation framework. Our approach employed probabilistic techniques to evaluate the likelihood of a slip

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in a given area and adjusted the weighting of contact probability sources based on their effectiveness in detecting slips across disjoint elevation changes. Building on the approach introduced in [13], we extended the framework to incorporate additional sources of probabilistic contact estimation, refined existing models to better account for perceived terrain and slip risk, and integrated terrain data directly into the contact evaluation process. The inclusion of these new probabilistic sensors allowed us to detect 100% of slips over 3 cm and 25% of slips under 3 cm. We also observed the false positive rate of slip detection drop to 39% of that observed when relying solely on end-effector velocity. We further validated our map-based analysis by comparing false positive rates when the foot was far from versus near a stair, observing a 40% reduction in false positives in low-risk areas. Overall, our method detected the onset of a slip within 32 ms and identified slip termination within 18 ms, demonstrating both rapid and reliable performance.

Although PACE improved slip detection on both flat and discontinuous terrain, several challenges remain. Future work includes optimizing PACE's meta-parameters to enhance both estimation accuracy and computational efficiency, following strategies such as those in [13]. In addition, integrating PACE with a vision-based machine learning terrain estimation model [18] could enable more predictive and adaptive contact reasoning, especially in unstructured or partially observable environments. Pursuing these directions will help increase the robustness and generalization of perception-aware slip detection for real-world legged locomotion.

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