Quantification and Optimization of Bipedal Locomotion on Rough Terrain

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***Abstract*— Measuring the stability of highly-dynamic bipedal locomotion is a challenging but essential task for more capable human-like walking. By discretizing the walking dynamics, we treat the system as a Markov chain, which lends itself to an easy quantification of failure rates by the expected number of steps before falling. This meaningful and intuitive metric is then used for optimizing and benchmarking given controllers. While this method is applicable to any controller scheme, we illustrate the results with two case demonstrations. One scheme is the now-familiar hybrid zero dynamics approach and the other is a method using piece-wise reference trajectories with a sliding mode control. In addition to low-level controller optimization, adopting a hierarchical control structure provides even more dramatic improvements on the system performance.**

I. DISCRETIZATION OF STATES FOR MARKOV CHAIN REPRESENTATION

Although walking motion is governed by hybrid dynamics, discrete impacts when a foot comes into contact with the ground provide a natural discretization of the robot motion, which motivates studying step-to-step dynamics of walking. Assuming finite probabilities for high enough disturbances encountered while walking, underactuated bipedal robots are destined to fall. In case the failure rates are low (but non-zero), walking is metastable for the system as shown in Figure 1.

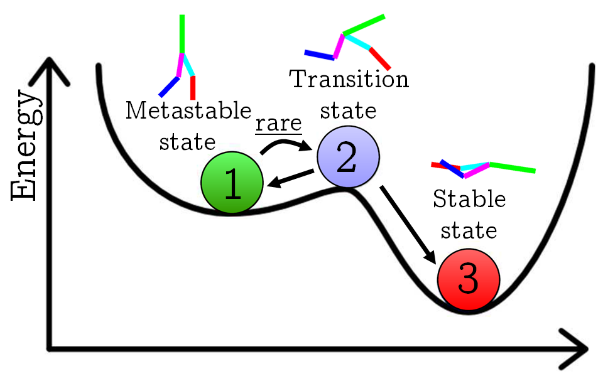

Fig. 1. Starting from State-1, the probability of moving to State-3 goes to 1 in time, so State-1 is not stable in the strict sense. However, if the transitions from State-1 to State-2 are quite rare, then it is misleading to say State-1 is unstable. In this case State-1 is said to be metastable. In this representative figure, State 1, 2, and 3 correspond to walking, stumbling, and failure respectively.

Given a walking controller and one-degree-of-freedom underactuation, the set of states which the robot may be found in at the end of a step turns out to be a quasi-2D manifold of the entire state space [1], which can be well-represented with a low number of states for our purposes. Then, assuming a stochastic terrain leads to Markov chain representation of the walking motion.

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II. STABILITY METRIC DEVELOPMENT

When the concern is stability, the walking motion can be approximated to consist of just two states as shown in Figure 2. The robot is able to take the next step without falling with probability λ_2, the second largest eigenvalue of the transition matrix associated with the original Markov chain in hand [2]. The remaining probability $(1-\lambda_2)$ maps the walking state to failure in the next step.

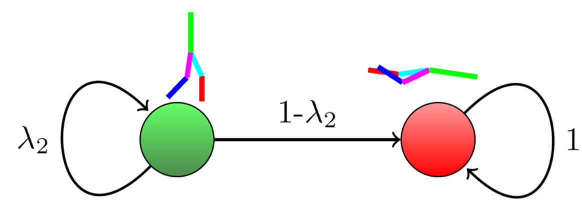

Fig. 2. Approximation of the walking dynamics. With λ_2 probability, the robot takes the next step successfully, it fails otherwise. λ_2 is the second largest eigenvalue of the Markov chain.

The structure given in Figure 2 allows easily calculating

$$\text{expected number of steps before falling} = \frac{1}{1-\lambda_2}. \quad (1)$$

III. OPTIMIZATION AND BENCHMARKING OF (LOW-LEVEL) CONTROL ACTION

Using the quantification in (1), the performance of a walking controller can be optimized or benchmarked. While this method is applicable to any controller scheme, we study two particular control strategies as case demonstrations. One scheme is the now-familiar hybrid zero dynamics (HZD) approach and the other is a method using piece-wise reference trajectories with a sliding mode control (SMC).

A. Optimization

We first optimize the performance of HZD control scheme as shown in Figure 3. As suggested in the original HZD paper [3], we first constraint speed to be 0.8 m/s and optimize for energy. We then remove the constraint and minimize the energy consumption. Finally, we optimize the controller's stability by using

$$\underset{\substack{\text{controller}\\\text{parameters}}}{\text{maximize}} \left\{ \begin{array}{c}\text{Expected}\\\text{Number of Steps}\end{array} \right\} = \underset{\substack{\text{controller}\\\text{parameters}}}{\text{maximize}} \left\{ \frac{1}{1-\lambda_2} \right\}. \quad (2)$$

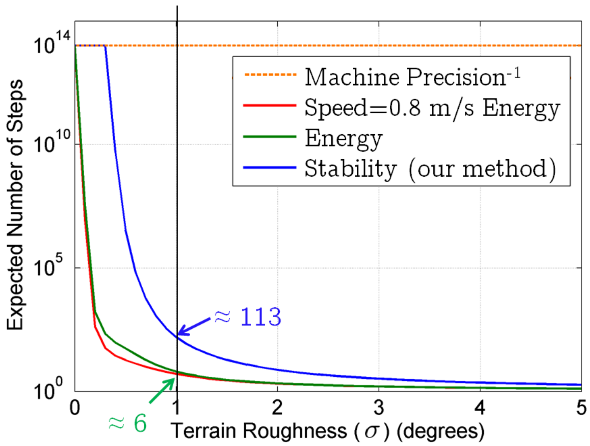

Fig. 3. Optimization of HZD control scheme. Slopes ahead of the robot are assumed to be normally distributed with $\mu = 0$.

To show the applicability of our method, we also optimize another controller scheme, which uses piece-wise reference trajectories with a sliding mode control (SMC). The results in Figure 4 shows great improvement in the system performance.

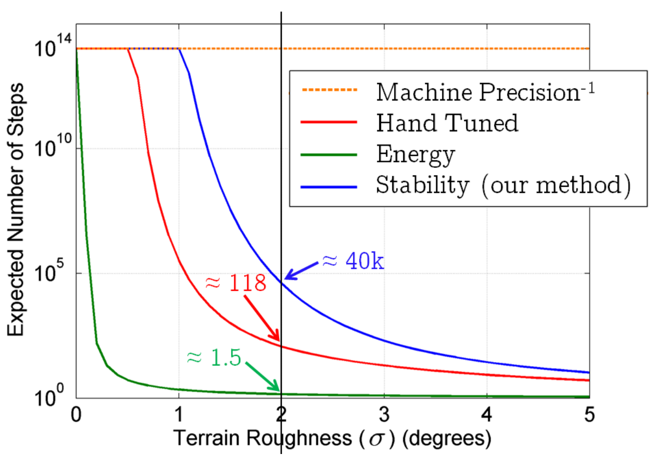

Fig. 4. Optimization of SMC control scheme. Slopes ahead of the robot are assumed to be normally distributed with $\mu = 0$.

B. Benchmark

The second use of (1) allows comparing different controllers' performances. In Figure 5 we benchmark the performance of the HZD and SMC controller schemes when they are optimized for stability. While this comparison is not fair to the HZD controller, because it is originally designed for flat terrain, our goal is to illustrate the benchmarking capability of our performance quantification.

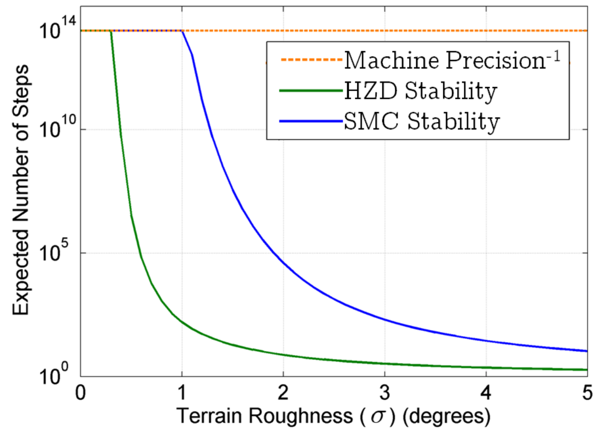

Fig. 5. Benchmarking of HZD and SMC control schemes optimized for stability. Slopes ahead of the robot are assumed to be normally distributed with $\mu = 0$.

IV. HIGH-LEVEL CONTROL DESIGN

One could easily imagine different controllers having various advantages under a variety of conditions, e.g., some controllers might walk better uphill, some may achieve the speed we desired, some may be more energy efficient, or others may have the step width we need. These controllers might be designed using different controller schemes and they can be optimized for different cost functions. A very intuitive idea at this point is to adopt a hierarchical control structure as shown in Figure 6. The high-level controller then choses the right low-level controller at each step using the optional noisy terrain estimation and state information.

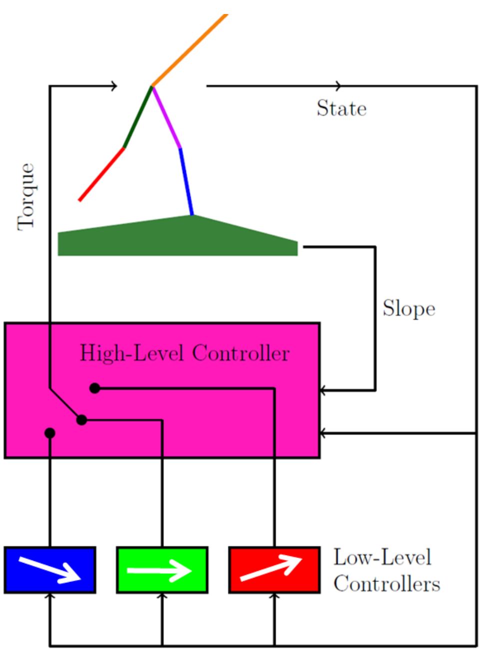

Fig. 6. Hierarchical control structure. The high-level controller then choses the right low-level controller at each step using the optional noisy terrain estimation and state information.

Figure 7 shows the resulting performance of adopting such a high-level control [4].

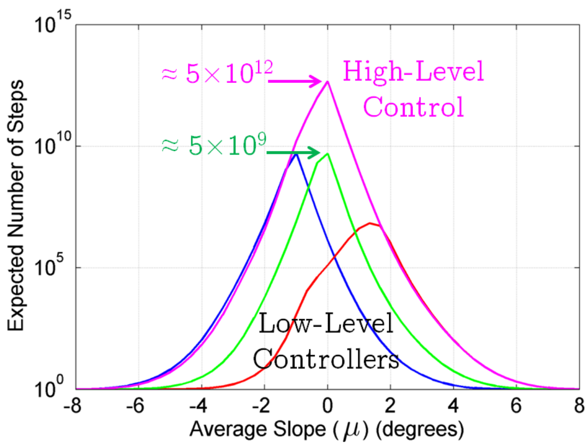

Fig. 7. The improvement of adopting a high-level controller drawn in Figure 6. Slopes ahead of the robot are assumed to be normally distributed with $\sigma = 1$.

ACKNOWLEDGMENT

This work is supported by the Institute for Collaborative Biotechnologies through grant W911NF-09-0001 from the U.S. Army Research Office. The content of the information does not necessarily reflect the position or the policy of the Government, and no official endorsement should be inferred.

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