Learning Stable and Energetically Economical Walking with RAMone

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Abstract— In this paper, we optimize over the control parameter space of our planar-bipedal robot, RAMone [7], for stable and energetically economical walking at various speeds. We formulate this task as an episodic reinforcement learning problem and use Covariance Matrix Adaptation [2]. The parameters we are interested in modifying include gains from our Hybrid Zero Dynamics style controller [8] and from RAMone's low-level motor controllers.

I. INTRODUCTION

Humans [5] and animals [3] use different gaits to locomote with energetic economy at different speeds. In our previous work [6], we found that the same was true for a detailed model of the planar bipedal robot RAMone (Fig. 1): walking was more economical for RAMone at low speeds, and running at high speeds. However, it remains to be seen if these simulated results extend to RAMone in hardware.

To this end, we used numerical optimization to find energetically economical gaits for a model of RAMone at various speeds [6]. This optimization involved minimizing the energetic cost of transport (CoT), the electrical work needed to travel a unit distance. The computed gaits described the optimal joint and motor trajectories as functions of time.

These optimal trajectories are not sufficiently stable when run in an open-loop manner on RAMone. One way to stabilize them, as we do here, is with a Hybrid Zero Dynamics (HZD) style controller, which synchronizes the controlled degrees of freedom to a phase variable [8].

An HZD style controller requires tuning a set of parameters, which at different speeds may have different values. Hand-tuning, although often used in practice, is time-consuming and may not lead to desired results. For example, we were unable to find parameters for stable walking at low speeds. Hand-tuning is likely to be even more of a challenge on hardware.

In this work, we explore an automated method to optimize over our parameter space at various speeds in simulation. We formulate this problem as an episodic reinforcement learning task. Our plan is to use the resulting control parameters to achieve stable walking in hardware.

II. METHOD

A. Parameter Space

For our walking controller, we follow a similar approach to [8], which relates the optimal trajectories, discussed earlier, to a phase variable (here, this is horizontal displacement of the upper body from the stance foot). This HZD controller
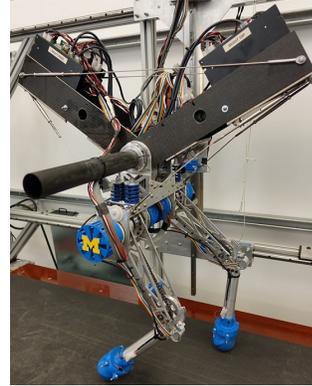
Fig. 1. The robot RAMone [7] is a five-link biped with series elastic actuation at the knees and hips, and rolling contacts at the feet. The robot is mounted on a planarizer system that restricts its motion to the sagittal plane [1]. The RAMone hardware is based on the ScarlETH leg design [4].

has two gains to tune: the foot clearance gain k_{fc} and the foot placement gain k_{fp}. The foot clearance gain modifies the swing leg's knee angle to change the height of the swing foot trajectory; the foot placement gain modifies stance leg's hip angle to control the next stepping location. We also tune two low-level gains of the system: the proportional error tracking gains k_{hip} and k_{knee} of the hip and knee motors. Lower gain values result in a more compliant controller; whereas higher gains result in a stiffer controller. These four gains

$$K = [k_{fc}, k_{fp}, k_{hip}, k_{knee}]$$

make up the parameter space for our optimization.

B. Optimization

To optimize over our parameter space, we use Covariance Matrix Adaptation, or CMA [2]. CMA is an iterative algorithm that uses stochastic sampling for a distribution of the optimization variables (parameters K here) described by a mean and variance. As CMA is iterated, a cost function is used to evaluate random samples of K and update the distribution so that it is centered around 'better' samples.

We choose CMA because it is more robust to local minima, when compared to gradient based methods. This is because CMA is stochastic and, thus, considers a wider range of sample states.

C. Evaluating Performance

We formulate our task as an episodic reinforcement problem. In our case, an episode refers to simulating

RAMone with a specific set of parameters K for a fixed time $t_{sim} = 7s$. An episode ends early if RAMone falls. At the end of an episode, the performance of the set of parameters K is evaluated with the following cost function:

$$Cost = \begin{cases} 100 + 20 \cdot \Delta t_{remaining}, & \text{robot falls} \\ 30 \cdot CoT + 1000 \cdot (\Delta \dot{x}_{des})^2, & \text{otherwise} \end{cases} \quad (1)$$

where $\Delta t_{remaining}$ is the amount of time between the fall and t_{sim}, CoT is the cost of transport (as calculated in [6]), and $\Delta \dot{x}_{des}$ is the difference between desired and actual speed of RAMone (average horizontal velocity of the main body). For the actual speed, we average over the last six steps.

The constants in the cost function were heuristically chosen to satisfy three criteria: 1) falling is always penalized more than walking; 2) falling earlier is penalized more than falling later; and 3) CoT and $\Delta \dot{x}_{des}$ have approximately the same weighted importance in the cost function.

D. Initialization of CMA

We compute optimal walking parameters K sequentially, for a range of different speeds. For each speed, we use CMA and the cost function (1); we initialize the CMA sample distribution using previously found optimal parameters K for an adjacent speed. For the speed of $0.4\,\mathrm{m/s}$ at the first iteration, CMA is initialized using hand-tuned parameters.

III. RESULTS AND DISCUSSION

With the approach described, we found control gain parameters K that produced stable walking of RAMone in simulation for speeds between $0.1\,\mathrm{m/s}$ and $1.0\,\mathrm{m/s}$. In contrast, when using hand-tuning, we were only able to stabilize walking at speeds between $0.4\,\mathrm{m/s}$ and $1.0\,\mathrm{m/s}$.

We found that the control parameters obtained through CMA yielded similar CoT, compared to the hand-tuned parameters, as shown in Fig. 2. There are two possible explanations for this: 1) The cost of transport does not depend strongly on the chosen parameters; and 2) our optimizer is getting caught in local minima and is thus not finding a more optimal solution. At the same time, the CMA-optimized controller performed better at desired speed tracking, compared to the hand-tuned controller, see Fig. 3.

To continue this line of work, we plan to use the parameters found through optimization to achieve stable walking on hardware. We also intend to modify the described method for application on hardware.

ACKNOWLEDGEMENTS
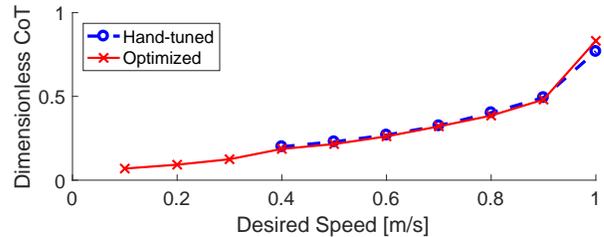
Fig. 2. The cost of transport (CoT) across different speeds for control parameters obtained through hand-tuning (blue) and optimization (red). The CoT is similar in both cases, however optimization was able to find parameters for stable walking over a larger range of speeds.
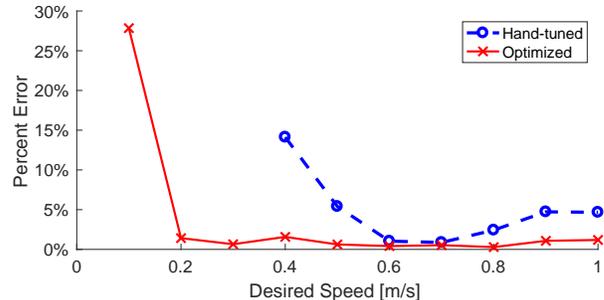
Fig. 3. The percent error of RAMone's speed in simulation against the desired speed using control parameters obtained through hand-tuning (blue) and through optimization (red). Optimized parameters track the desired speed more accurately than hand-tuned parameters across all speeds.

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