Rethinking about robustness in legged-robotics co-design

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***Abstract*— The problem of designing complex robotic hardware using numerical optimization got significant attention in recent years. However, ensuring robustness, which is essential to guarantee the practical applicability of the designed solutions, remains an ongoing challenge in co-design. This problem becomes particularly pronounced when dealing with inherently unstable systems, such as legged robots. In this extended abstract, we want to reason about these challenges and investigate possible solutions to tackle such a problem based on current trends in the community.**

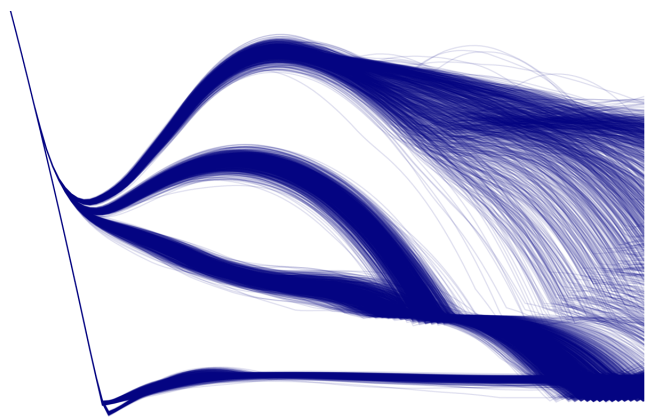

Fig. 1: Illustration of the deterministic chaos arising from a forward simulation with contacts: several different trajectories are possible for slight changes in the model parameters. Co-design for robustness needs to reason about how hardware selection impacts this evolution.

I. Robot control robustness as morphological computation

Morphological computation [1] is a concept borrowed from biology that suggests offloading certain computational tasks to the physical body rather than relying solely on onboard computational resources. This idea has gained traction in robotics as a means to achieve more robust and efficient control systems. For instance, for a legged robot stepping on an uneven surface, we would like to provide the same signals that we would do in normal conditions and let its mechanical structure take care of the unplanned perturbations. In the context of robot control, morphological computation hence involves designing robots with physical features that can exploit the dynamics of the system to simplify control tasks and enhance performance. Co-design, when coupled with the principles of morphological computation, offers a holistic approach to developing robots with these capabilities. By integrating the design of the robot's body and its control logic, co-design can be used to achieve robust and adaptive behavior in complex and dynamic environments.

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II. Robustness in co-design

Most of the prior research in the co-design primarily focused on optimality, as outlined in previous work [2–5]. However, factors such as unmodelled dynamics, noise, delays, saturation, or actuator dynamics can prevent the system from effectively rejecting external perturbations. Thus, while optimality still remains a fundamental criterion, robustness emerges as a complementary aspect that must be addressed to deploy these solutions effectively in the real world. The co-design of a legged system, which can robustly operate also in unplanned scenarios, is still an open problem. One of the directions in our current work is the selection of trajectories and designs that require the least control correction when replayed on real hardware. To achieve this goal, several strategies have been proposed in the past, including stochastic optimization [6, 7] and data-driven approaches [8]. In the last work, a robust bi-level scheme was proposed, incorporating additional simulations to enhance the robustness of the co-design process. Such a technique was used to select the optimal hardware parameters for robustness, namely those resulting in a trajectory and local controller that could better perform in simulation with unplanned disturbances. The main drawbacks of the approach were scalability, and the selection of a locally optimal controller which was not explicitly optimized for robustness. In another work, [9, 10], in order to handle robustness, the maximization of the region of attraction of a stabilizing controller has been investigated for simple underactuated systems. Finally, concerning parametric optimization, in [11] a method has been outlined to select optimal trajectories. This work achieved the selection of robust references for UAVs thanks to sensitivity analysis. The differential flatness property of these robotics systems shifts the problem of robust control to robust trajectory selection. On the other hand, for legged robots, with more DoFs and switching contact dynamics, the applicability of such a method must be carefully reconsidered.

III. Reasoning about robustness in contact-rich problems

To achieve similar results to [11] in legged-robotics, but several challenges arise given that the problem is inherently non-smooth. Questions that remain still open and have to be investigated are:

- What is the right metric to define and optimize the robustness of a design?
- Are sensitivies a good starting point or should statistical-based sampling be used instead?
- How to obtain meaningful gradients through the simulation, which features a non-differentiable dynamic?
- Can a method compute these sensitivities efficiently and be scalable to the dimensionality of legged-robots?
- Can the non-linearity of the system with contacts be properly modelled and handled?
- In the case of sampling-based methods, can we compute the robustness metrics efficiently?

To reason about these open problems, we are investigating different ideas to understand what is the most suitable method to include a robustness metric in co-design considering the robot's mechanical design and its controller. The open research investigations are related to:

a) Leveraging differentiable simulation: Parametric gradients could be obtained via differentiable simulation [12, 13]. However, the gradients obtained for loco-manipulation problems are notoriously ill-conditioned as they rely on relazations and are obtained through a stiff dynamic [14]. As a possible remedy to this, incorporating smooth differentiable formulation may help to recover better-conditioned jacobians [15]. However, also in this case, several complications arise and need to be considered carefully, as noted in [16], gradients are not always sufficient and in such cases black box methods may be used to obtain smoothed proxies for loss functions. The authors acknowledge several potential issues in computing gradients through dynamical systems, such as numerical precision, memory requirements, and flat loss landscapes (typical in loco-manipuation problems).

b) Leveraging parallelization: Another solution hence would be to use massive parallelizable simulation to better approximate gradients through sampling, similar to what has been currently a successful trend for simulation in reinforcement learning [17]. Moreover the use of parallelization also opens the road to the use of hybrid methods, combining analyic and sampled gradients.

c) Multimodality, singularity and bifurcation points.: Contact-rich problems show the property of deterministic chaos. Depending on the initial conditions, very different outcomes may arise. The selection of a method and a metric that can overcome this difficulty may be tailored for the practical co-design optimization. For instance, if the final state of a perturbed simulation becomes multimodal, then appropriate mathematical tools would be necessary to tackle the stochasticity into account as distributions. In our current developements this problem is being carefully treated.

IV. Perspective Work

Integrating morphological computation principles in robot design offers a promising pathway for advancing robotics toward enhanced robustness and adaptability. Optimizing both the robot's physical design and its control algorithms will be fundamental to achieve reliable performance across various environments. However, navigating through the challenges of this co-design problem and selecting the most suited robustness formulation will be crucial as explained in the previous section. The problem of contacts is currently a big obstacle to overcome. Moreover the selection of metrics related to robustness has been quite overlooked in the past, also due to the non-linear nature of the problem. The synthesis of a robust design is hence still an open problem, which has to be tackled to improve the deployability of robots. However the current advancements in trajectory optimization and learning pave the way for a more reliable investigation of the problem in the future.

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