Toward Engineering Mechanical Intelligence via Scalable Co-design

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I. Introduction & Background

A frequent goal in robot design is to engineer mechanical intelligence into the systems we field, and as often empirically observed in biological systems. Such embodied intelligence should translate into the effective interaction between a robot and the environment, enabling more efficient and robust locomotion. Yet, it remains an open problem for how designers can achieve this goal through formalized methods. Robots are composed of both mechanical and control systems, which are often designed separately. This work proposes that considering the coupled aspects of both systems simultaneously via co-design provides a route for embodying intelligence into the morphological design decisions. Nonetheless, the coupled consideration of morphology and control introduces scalability challenges for co-design methods. This work co-optimizes a feedback controller with the system morphology for a hopping robot, and provides a method that deals with scalability via the Alternating Direction Method of Multipliers (ADMM). The embodied intelligence of the design is assessed via considering the capacity of the system's natural dynamics toward reducing the control action required to reject disturbances.

II. Methods

To add robustness reasoning to a design, we co-optimize morphology parameters $\boldsymbol{\rho}$, a nominal state-control pair $\boldsymbol{\gamma}^*(t)$, and linear feedback gains $\mathbf{K}(t)$ for disturbance rejection. Using a two-stage SP formulation [1], the co-design framework makes decisions over a probabilistic model of disturbances $\boldsymbol{\omega}(t)$ to a nominal scenario. To relieve scalability limitations as the number of scenarios increases, ADMM [2] is considered to coordinate the solution of reduced-size SP problems (with few scenarios) that in total add to a large-size SP problem (see Fig. 1a). For co-design, consider that there exists a single projected (global) design and several designs produced by the local sub-problems. The ADMM creates design consensus by ensuring that local and global variables are consistent.

III. Results & Discussion

For a planar 5-DoF monopod robot, we tested the framework with 10 scenarios encoding terrain-height disturbances. Height changes were modeled as stair obstacles with touch-down at a random time ($\sim \mathcal{N}(0.8, 0.25) \in (0.5, 1.0)$) during flight. The problem targeted the minimization of the jump time and the electrical energy of the DC motors actuating the hip and knee joints, and included the link geometry and the motor gear ratios as decision variables. Each ADMM sub-problem included the nominal (i.e., flat-terrain) scenario and one perturbed scenario. After 26 ADMM iterations, the global and local trajectories converged to an acceptable accuracy (see Fig. 1b). The co-optimized controller and feedback gains were effective in stabilizing the robot. Fig. 1c shows phase plots that confirm the stabilization of the knee states. The results agree with [3]: co-optimizing the nominal trajectory and the feedback controller shrinks the region where the post-impact states occur, which reduces the control effort. On average, the cost of transport (CoT) increased 15% above the nominal using the proposed approach, while using LQR designed independently of the nominal trajectory and the morphology, the CoT increased $\approx 100\%$. The lower energy use needed for stabilization can be an indicator of embodied intelligence.

For robot co-design, the ADMM implementation here is the first of its sort. Our previous implementations without ADMM became computationally intractable after including more than 6 disturbed scenarios. The additional scenarios available from the improved scalability of ADMM improved both robustness and efficiency. Future work will investigate convergence and optimality conditions, and corroborate the contribution of the robot's natural dynamics to the control-effort reduction.

References

[1] G. Bravo-Palacios *et al.*, *IEEE Robotics and Automation Letters*, 2020.
[2] S. Boyd *et al.* Now Publishers Inc, 2011.
[3] H. Dai *et al.*, in *51st IEEE Conference on Decision and Control*, 2012.

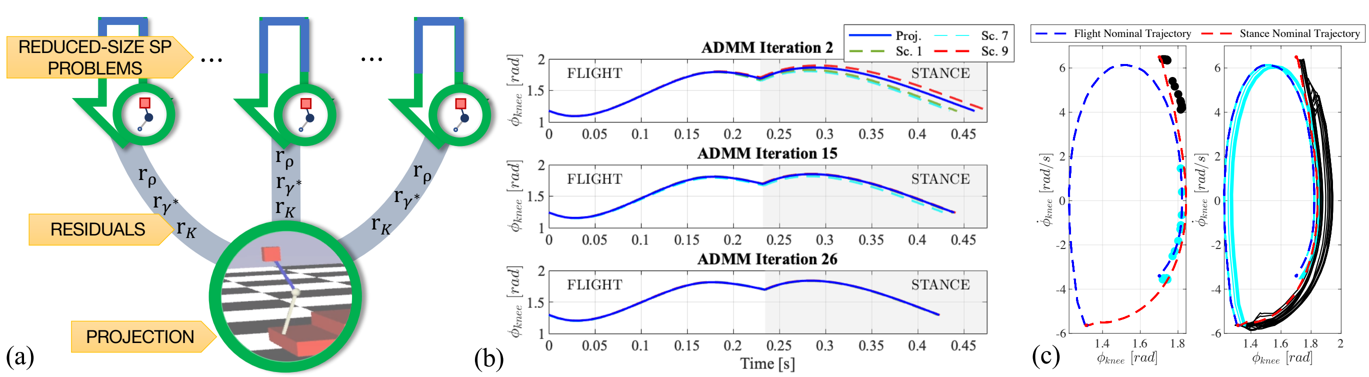

Fig. 1. (a) Co-design of a 5-DoF monopod robot: The ADMM breaks the SP problem into reduced-size problems. (b) Nominal knee-angle trajectories of global (Proj.) and 3 local (Sc.) designs after ADMM iterations 2 (top), 15 (middle), and 26 (bottom). (c) Knee phase plots: (left) Cyan and black dots mark pre- and post-impact states, respectively, for the disturbed scenarios. (right) Stabilized trajectories correspond with the dots from the left.