Full-Body Optimal Control of a Swimming Soft Robot Enabled by Data-Driven Model Reduction

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I. Introduction

Anguilliform swimming is an effective mode of locomotion utilized by elongated fish like eels and oarfish to travel long distances. It is characterized by the use of full-body undulations that produce thrust and it proves highly energy efficient [1]. The efficiency and morphological simplicity of anguilliform fish make anguilliform swimming a promising swimming for aquatic robots that require long-duration operation. However, the efficiency of anguilliform swimming is a product of the coupled dynamics of the swimmer's soft-body and surrounding water. In order to enable this level of efficiency on a robotic platform, the robot must implement online control that considers these coupled dynamics in real time. A model predictive control (MPC) framework lends itself well to considering these coupled physics. However, the high-fidelity soft-body simulation and fluid simulation required for effective MPC proves too computationally expensive for real-time control.

In this work, we leverage data-driven model reduction techniques to enable approximate physics simulation and high-speed MPC of a simulated, soft, anguilliform robot (Fig. 1). We conduct a comparative study of multiple methods for linear model reduction, allowing us to assess their efficacy in both the state estimation and control context to allow the robot to mimic well-studied, straight-line swimming gaits of anguilliform fish [1].

II. Methods

A. Robot Simulation

The simulated robot is comprised of three antagonistically-actuated soft segments that are attached to each other by rigid couples. The simulation was implemented in the Simulation Open Framework Architecture (SOFA) and only considers the solid body mechanics of the system. The full-order model has 226,941 states and exhibits nonlinear dynamics. Through singular value decomposition of a snapshot matrix of state trajectories, we found that 94% of the state variance is contained within a 12-dimensional linear subspace of the state space. This motivates us to construct non-intrusive reduced-order models (ROMs) that learn linear time-invariant systems.

B. ROM Synthesis

We conduct a comparative study of multiple ROM methods in the context of state estimation and full-body control of the soft anguilliform robot. The compared methods include the Eigensystem Realization Algorithm (ERA) [2],

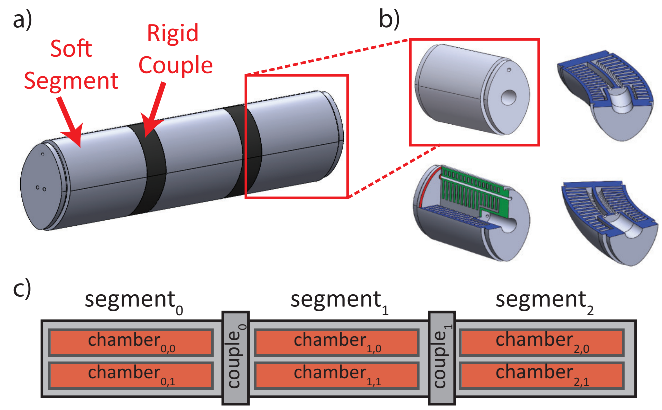

Fig. 1. Design of three-segment robot for anguilliform swimming. The soft robot (a) is comprised of multiple soft segments that each contain two antagonistic fluid elastic actuators (b). The robot is arranged by attaching segments with rigid couples (c).

Dynamic Mode Decomposition with control (DMDc) [3], and Lagrangian-preserving Operator Inference (LOpInf) [4]. These methods were selected as representative methods for various classes of data-driven model order reduction techniques that prove common in the modern soft-robot modelling literature. During each simulation episode, inputs were generated from a Brownian random process. The output of the system is considered to be the centerline of the robot and is computed by averaging the position of the 3D mesh points close to the sagittal plane of the robot. The inputs, system state, and outputs are then used to construct a data set comprised of 30 episodes, each with 200 time steps of 0.001 second. As implementations of ERA take a single impulse response as input, the Observer Kalman Filter Identification algorithm [5] was first used to compute the impulse response that optimally fits the input-output response of the first episode. The remaining ROMs were constructed from snapshot matrices of the first five episodes in the dataset, leaving the remaining 25 episodes for validating the ROMs.

C. Observer Synthesis

We first evaluated the capacity of each model for open-loop prediction of the systems output response to random inputs. We found that LOpInf demonstrates the least normalized error over the prediction horizon of 200 timesteps (Fig. 2) across both datasets. Each model was then used to synthesize a closed-loop state observer with linear output injection. As expected, each closed-loop state observer provided lower prediction error than their open-loop counterparts (Fig. 3). We then used the the projection mappings provided by DMDc and LOpInf to assess if the state observers effectively track the full-order state. In this case we found that the quality of full-order state prediction degrades in the closed-loop observer based on the DMDc ROM while the LOpInf observer maintains high-quality tracking of the full-order state (Fig. 3b).

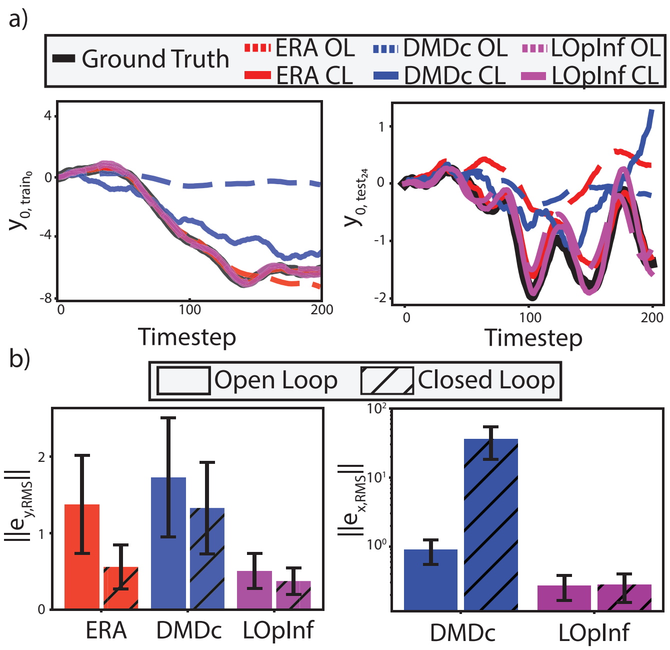

Fig. 2. State prediction performance of each ROM. (a) Example trajectories showing the open-loop (OL) and closed-loop (CL) observer prediction in a training trial (left) and test trial (right). (b) RMS errors were computed over every trial for output prediction (left) and full-order state prediction (right) for both open-loop and closed-loop observers.

D. *Control Optimization*

Finally, we constructed a receding horizon controller based on each ROM that, given a reference output trajectory, computes the optimal control inputs via quadratic program. Reference trajectories were constructed based on past work on anguilliform fish [1] (Fig. 3a). To compare each of the controllers, we computed the RMS output tracking error and input behavior for each controller over 500 timesteps. The controllers using ROMs from ERA and LOpInf both resulted in low tracking error and energy usage. Both controllers also revealed an underactuated control strategy that most heavily actuated the first segment so as to induce body undulations that then propagate down the rest of the robot's body.

III. Visions

In comparison to modern autonomous underwater vehicles, which are often propeller-driven, soft swimming robots provide a quieter and safer solution to underwater exploration. This safety is due to their material compliance and actuation mechanisms, making it more difficult for them to damage animals and their environment in the case of collisions. Through this work we demonstrate a framework for full-body control of soft swimming robots, which presents a solution to the problem of high dimensionality that is often experienced in of soft-robot control. Future work could construct coupled ROMs that express the soft robot's dynamics as well as the dynamics of surrounding water, enabling MPC that simultaneously optimizes the soft robot's gait and its fluid dynamics to mimic those of natural swimmers. Future work could also leverage simulation-based data to synthesize controllers that can then be transferred to experimental system. Through continued work on reduced order modelling and the problem of simulation-to-reality transfer, we anticipate that aquatic soft robots will enable transformative impacts on deep sea exploration.

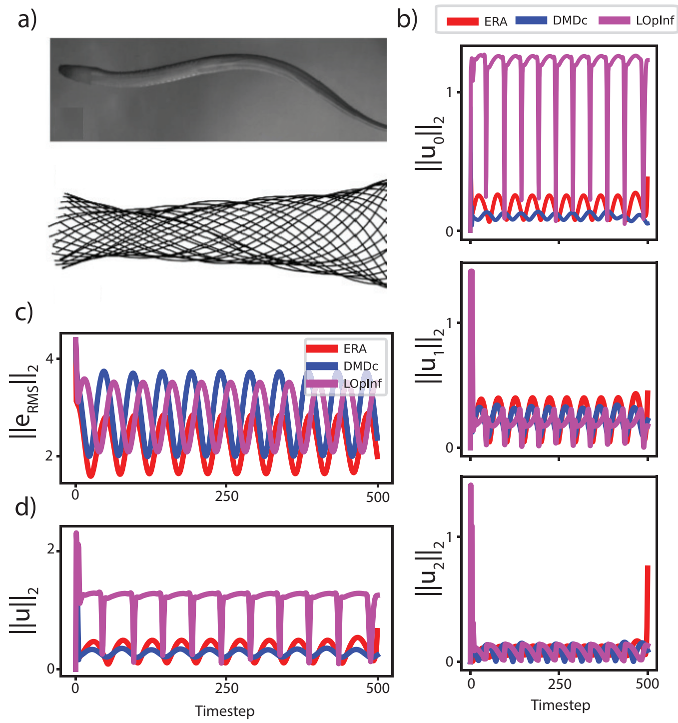

Fig. 3. Performance of ROM-based controllers. (a) Reference trajectories and the image of an eel are drawn from past work on anguilliform motion [1]. (b) The total input energy computed from each controller was computed as a function of time, showing an actuation strategy that heavily actuated the first segment. (c) Total RMS tracking error was computed for each method (c) along with the total input energy (d) as a function of time.

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