Research Statement

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Recent advances in computational power and numerical control algorithms have enabled robots to execute complex, precise motions across a wide range of applications. In particular, numerical trajectory optimization methods are widely used to generate task-specific solutions [1], and learning-based control methods [2] allow robots to generate efficient motions without explicit models by learning from input-output data. However, these approaches often focus on optimizing individual motion strategies without explicitly characterizing the fundamental motion principles—such as how locomoting systems generate displacement through cyclic shape changes or how optimal motion strategies adapt to external forces—thereby hindering the development of more generalizable and interpretable motion strategies.

My research develops geometric insights into optimal motions and derives control strategies by integrating geometric mechanics and Riemannian variational calculus. Geometric mechanics [3] provides an intuitive framework for understanding motion principles, such as the net displacement generated by joint trajectories. Riemannian variational calculus (often appearing as the indirect method of optimal control) reveals the optimality conditions necessary to generate efficient motion by characterizing a system's dynamics through Riemannian geometry. This statement outlines my research contributions, along with potential directions for extending my current work.

Past & Current research

My research examines the joint-level dynamics of robotic systems and their resulting motion strategies, focusing on two key categories: locomoting systems and manipulators. Locomoting systems generate body motion through internal shape changes (i.e., gaits), as exemplified by a three-link swimmer navigating a viscous fluid using steering gaits (Figure 1(a-b)). Each gait incurs a cost, such as dissipated power or actuation effort, and optimal motions maximize displacement relative to this cost. While selecting appropriate gaits to achieve desired motions, a mid-level controller regulates gait transitions to ensure smoothness and efficiency. By analyzing locomoting systems, I have investigated **optimal gait families for generating diverse net displacements** and **geometric principles of optimal gait transitions**.

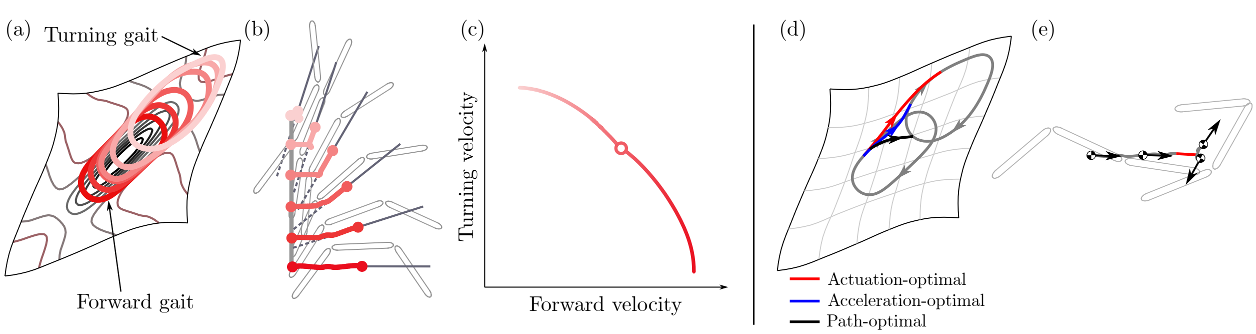

Figure 1: (a-c) Steering Pareto-front gait family of Purcell three-link swimmers. (a) Optimal gaits in metric-weighted joint space, with level sets of the forward displacement function. The metric-weighted path length represents effort, and the enclosed signed area determines net displacement. Red and pink cycles indicate forward and turning gaits. (b) Corresponding body trajectories. (c) Pareto front in forward-turning velocity space at given effort levels. (d-e) Optimal gait transition from forward to turning motion. (d) Three gait-switching trajectories in metric-weighted joint space. (e) Corresponding body trajectories.

Robotic manipulators, in contrast, achieve precise motion through coordinated joint trajectories that directly govern end-effector movement. Their dynamics and optimal motions are significantly influenced by external forces such as gravity and friction. For example, optimal motions under gravity adapt to the downward pull, while those under velocity-dependent friction follow the shortest path to minimize resistance. I have explored **the fundamental properties of optimal trajectories under external forces**.

Optimal Gait Family

A gait library [4] consists of discrete, optimized gaits that enable systems to reach desired positions (controllability [5]) while minimizing gait transitions (maneuverability [6]). Expanding on this concept, my work focuses on **gait families** [7, 8]—**continuous mappings that associate control parameters with gaits** corresponding to specific step sizes and steering rates, thereby enhancing both controllability and maneuverability through continuity.

I developed **a framework to generate optimal gait families without individually optimizing each gait**. This framework includes two compensation methods: 1) A local search method using nonlinear parametric programming to construct smooth Pareto front curves that maximize forward and turning velocities when both cannot increase simultaneously. 2) A global search method that ensures robustness near bifurcation points (e.g., multiple solutions), enabling smooth and adaptable transitions across the gait family. These approaches allow us to generate continuous steering gait families, as illustrated in Figure 1(a-c).

Optimal Gait Transition

To integrate optimal gait families into motion planning, I developed a **gait transition trajectory generator based on a Riemannian variational calculus** [9]. I analyzed gait transition dynamics and their costs, considering Riemannian geometry: metric-weighted pathlength for drag-dominated systems and Riemannian curvature for inertia-dominated systems to capture second-order effects. Three optimization objectives were defined: **path-optimal** (minimizing kinetic energy), **acceleration-optimal** (ensuring smooth transitions aligned with natural dynamics), and **actuation-optimal** (minimizing actuator torque by accounting for physical configuration of the actuators). These approaches enable smooth, efficient, and adaptable gait transitions, as illustrated in Figure 1(d-e).

Geometric Effects of External Forces on Optimal Trajectories

To extend the geometric optimal control framework to general robotic systems, I refine **analytical tools to explain how external forces (described by a function of joint position and velocities) influence optimal trajectories** [10]. The key findings are: (1) Optimal trajectories of mechanical systems depend on the curvature of the Riemannian manifolds defined by kinetic energy metrics. (2) Optimal trajectories under **potential forces** (e.g., gravity, elastic forces) are shaped by the curvature of potential fields on the manifold. (3) **Drag forces** (e.g., friction) cause the straightening effect of optimal trajectories, minimizing drag-metric-weighted pathlength. Based on these approaches, I analyze the optimal trajectories

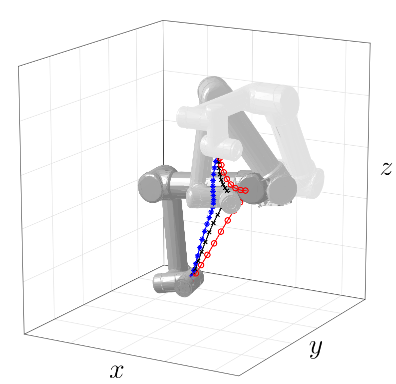

Figure 2: Actuation-optimal trajectories: Baseline (black), With gravity effects (red), With drag effects (blue).

of 6-degree-of-freedom robotic manipulators with gravitational
and joint friction forces, as illustrated in Figure 2.

Research Goal and Future research

My research provides an analytical framework for understanding robots' optimal dynamics. My long-term goal is to refine this framework to handle complex dynamics and develop practical control algorithms for real-world applications through a geometric understanding of motion.

Building on my previous work, I aim to **develop an interface that integrates offline-optimized gaits with high-level motion planning to achieve agile and robust motion control and planning** [11, 12]. By leveraging continuous optimal gait families and their smooth transitions, this approach reduces problem complexity, allowing conventional planners to focus on a single rigid-body (SRBD) motion. This advancement will enable robotic locomotion systems to dynamically adjust their plans, broadening their application scope while ensuring computational efficiency.

Furthermore, I am interested in **enhancing control robustness against disturbances using geometric tools**. While my previous work has focused on the geometric understanding of optimal robot motion, real-world control design requires robustness to uncertainties. Geometric and analytical tools provide intuitive insights into stability and resilience. For example, the *control contraction metric* represents stability as Riemannian energy and evaluates robustness against unknown dynamics [13]. Combined with my previous work, these insights will aid in designing controllers that generate optimal and robust robot motions.

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