Karlsruher Institut für Technologie

Invented for life

Autonome Lernende Roboter (ALR)

Prof. Gerhard Neumann

Project Type

- ☑ Master Thesis
- ☐ Bachelor Thesis
- ☐ Research Project

Supervisors

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Difficulty

Algorithmic

Math

Application

Geometry-based Robot Motion Learning

Description

In this project, we want to study different aspects of motion learning approaches that use geometry to formulate learning and reconstruction of complicated robot trajectories. For doing so, we will select the most promising approaches in the current literature such as [1, 2, 3, 4] and analyze them theoretically and analytically from a common geometrical perspective.

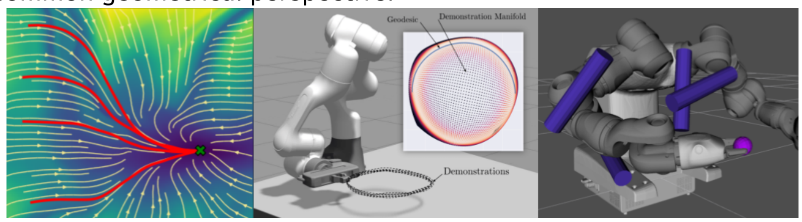

Figure 1: *Left:* Velocity vector field used to reconstruct learned motion [3]. *Center:* Riemannian metric learned from circular robot motion and geodesic used to reconstruct the motion [1]. *Right:* Robot reaching a point in the task space while avoiding multiple obstacle [4]

In this project, we want to investigate how such methods can be used for learning complex motion skills that require a deep understanding of the dynamics of the robot and the environment. Also, we are interested to see how advantageous the ideas behind these methods are when imposing external restrictions such as obstacle avoidance. In this master thesis, we will analyze the common mathematical foundation of all these methods defining their fundamentals such as the underlying structure of the latent spaces, embedded manifolds, metrics and mapping functions for methods such as [1] in addition to the formulation of the vector fields in methods that consider the dynamics of the motion such as [3, 2, 4]. As the final step, we will exploit our knowledge to combine different advantageous properties of these methods to formulate a unified geometric robot motion framework.

Tasks

The tasks in this project will involve:

- Implementation: Getting the approaches in [2, 3, 4] to work on our robot system and simulation framework. Code and Simulation of [3, 4] are available, albeit using a different simulator and robot.
- Benchmarking: Testing the algorithms on our toy benchmarks such as English letter dataset and robotic settings in real and simulation environment.
- Analysis: Investigating the common mathematical foundation of mentioned approaches regarding their underlying geometric structure of latent spaces, embedded manifolds, vector fields, and associated mapping functions and metrics.
- Unified framework: Consolidate the achieved knowledge from previous tasks to formulate a unified framework that perceives the problem of robot learning and generation from a geometric perspective.

References

[1] H. Beik-Mohammadi, S. Hauberg, G. Arvanitidis, G. Neumann, and L. Rozo. Learning riemannian manifolds for geodesic motion skills. In *Proceedings of Robotics: Science and Systems*, July 2021.

[2] Emile Mathieu and Maximilian Nickel. Riemannian continuous normalizing flows, 2020.

[3] M. Asif Rana, Anqi Li, Dieter Fox, Byron Boots, Fabio Ramos, and Nathan Ratliff. Euclideanizing flows: Diffeomorphic reduction for learning stable dynamical systems. *arXiv*, 120:1–10, 2020.

[4] Nathan D. Ratliff, Jan Issac, Daniel Kappler, Stan Birchfield, and Dieter Fox. Riemannian Motion Policies. *arXiv*, 2018.