Motion Synthesis on Learned Skill Manifolds
Ioannis Havoutis, Subramanian Ramamoorthy

Motivation
Humanoid robots are extremely flexible and complex platforms. We want them to be able to exhibit a variety of dynamical behaviours subject to:
• Task constraints (Feasibility)
• Large disturbances (Reactive planning)

For this we need a flexible motion representation that would allow us to handle the complexity of the environment and the inherent complexity of the system.

How to represent Skills?
• Families of paths in state space defined by system and task constraints.

Sampling based motion planning
Rapidly-exploring random trees [1] is one of the most successful sampling based motion planning algorithms. Part of its success can be attributed to the computational simplicity and fast explorative nature.

mRRT: Motion planning on manifolds
Leveraging skill-relevant knowledge in the form of a learned manifold into the planning process [3] we:
• Bias exploration towards known good solutions
• Focus exploration where it really matters

Results
• Start from three demonstrated trajectories for each of the three tasks (step forward, kick, step backward)
• 10 trials for each task/algorithm
• No analytical model of the robot (evaluate samples in simulation)

Generalizing to unseen trajectories:
• 57.6% less invalid samples
• 25.2% decrease in overall planning steps

Why pay the computational cost of mRRT?
• Representation that captures all feasible solutions
• Enables layered strategies
• Basis for Optimal Control over manifold
• Composition of skill-manifolds

References: