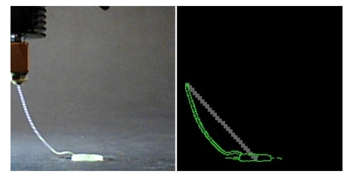
Tool Path Planning for Freeform 3D Printing with Deep Reinforcement Learning

1 Objective



Freeform 3D printing is an innovative additive manufacturing process, which creates 3D curves in aerial space instead of 2D layers [1]. In the freeform 3D printing process, there is a trade-off between printing speed and printing accuracy. At a low print speed, the material has sufficient time to solidify before a new layer is added so that a high printing accuracy can be achieved. As the printing speed increases, the hot filament can be easily deformed under gravity and the printing accuracy decreases. The objective of this work is to find the trajectory for the extruder that can neutralize the effect of gravity and build a filament with the desired shape.

2 Related Work

The dynamic thermomechanical response of the extruded filament material as the extruder moving in aerial space was studied by Zohdi [3], and a model-based planning method was developed. In this model-based planning method, the increments of the extruded filament are represented by a continuously growing number of small particles in the finite element analysis, which means the computational complexity is exponential to the filament length. Another model-free algorithm called deep deterministic policy gradient (DDPG) [2] adapts the ideas underlying DQN to continuous action spaces. However, a direct application of this model-free reinforcement learning algorithm needs a time-varying deep neural network approximator to estimate the actor-value function (Q function), because the desired filament shape is varying from time to time.

3 Technical Outline

As with feedback control, we introduce the state reference s_r that will help us define the reward function to guide the policy learning. The state reference is the projection of the desired filament curve to the state space. In this way, the reward function $r(s, s_r, a) : \mathcal{S} \times \mathcal{S} \times \mathcal{A} \to \mathbb{R}$ becomes time-invariant, because all the time-varying factors are included in actual states, state references and actions. With the rewards, policy and action-value function defined on the augmented state space $\bar{\mathcal{S}} = \mathcal{S} \times \mathcal{S}$, the DDPG algorithm can be implemented to find the tool path to create 3D objects.

References

[1] S. Jokic and P. Novikov. Mataerial-a radical new 3d printing method. *Retrieved September*, 15, 2016.

[2] T. P. Lillicrap, J. J. Hunt, A. Pritzel, N. Heess, T. Erez, Y. Tassa, D. Silver, and D. Wierstra. Continuous control with deep reinforcement learning. *arXiv preprint arXiv:1509.02971*, 2015.

[3] T. Zohdi. Dynamic thermomechanical modeling and simulation of the design of rapid free-form 3d printing processes with evolutionary machine learning. *Computer Methods in Applied Mechanics and Engineering*, 331:343–362, 2018.