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MULTI-LINK ROBOTIC MANIPULATOR GUIDANCE VIA MACHINE LEARNING ALGORITHMS FOR MARS EXCAVATORS

Abstract

Surface exploration missions are essential to better understand the evolution of the Solar System. Indeed, Mars represents a unique environment due to its similarities with the Earth. Investigating its surface is also crucial to retrieve information about the presence of water on the red planet. Several missions have already been launched to study and analyze samples from the surface, such as Opportunity, Curiosity, and Perseverance, just to mention a few. Other missions are also planned to be launched in the future to eventually bring some samples back to the Earth. The task of analyzing the samples is usually performed by robotic manipulators mounted onboard landers and rovers. The future need of increasing the autonomy of robotic missions with respect to the ground control stations, especially required in presence of communications delay, represents a current challenge to address. In particular, machine learning algorithms seem promising in facing this problem. Thus, this work aims at studying multi-link robotic manipulators guidance via machine learning algorithms. In fact, a robotic excavator, made up of three robotic arms (links) and the end effector, is considered. In order to plan its trajectory, an optimal control problem minimizing the energy associated to the control torque applied to each joint is faced. Two different machine learning approaches will be considered. The first one is Reinforcement Learning (RL), which is proved to be reliable enough even in case of different initial and final conditions and random events, thus achieving the goal of increasing the decision autonomy of the robotic manipulator. The second approach is based on a recent Physics-Informed Neural Networks (PINNs) framework called Extreme Theory of Functional Connections (X-TFC), which has been demonstrated to be accurate in learning the solution of optimal control problems. Moreover, the two approaches could also be combined by generating samples trajectory with RL to be included within the training process of PINNs. Once trained, the Neural Networks will be deployed to analyze different simulation scenarios. Comparisons between the two methodologies will be carried out to highlight the corresponding performances in terms of optimality of the results, training time, and computational time, with the possibility to exploit the frameworks for real-time applications.