IAF SPACE SYSTEMS SYMPOSIUM (D1)
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Author: Mr. Arash Nourimand
MDA SPACE INC., Canada

Mr. Malav Naik
MDA SPACE INC., Canada
Mr. Himanshu Sharma
MDA SPACE INC., Canada
Mr. Nader Abu El Samid
MDA SPACE INC., Canada
Mr. Alex Vargas
MDA SPACE INC., Canada
Dr. Paul Grouchy
MDA SPACE INC., Canada

USE OF MACHINE LEARNING TO OPTIMIZE MECHANISM DESIGN FOR SPACE ROBOTICS APPLICATIONS

Abstract

As the frequency and need for complex space missions increases, the ability to rapidly make spacecraft infrastructure robust to meet this demand is imperative. As part of the Lunar Gateway mission, MDA's contribution for Canada - Canadarm3, is a next-generation robotics system with advanced functionality on a deep space outpost orbiting near the moon. Due to the advanced robotics necessary to function in lunar orbit, the rigorous engineering requirements imposed on the system, and the ambitious timeline to develop the hardware, the design and verification methods used for engineering such a system must be enhanced.

To ensure rapid development of robotic mechanisms for Canadarm3 and beyond, MDA's Robotic and Space Operations (RSO) division has developed an optimization pipeline for automated generative design. This methodology complements the current practice of Computer Aided Design and Engineering (CAD and CAE, respectively), and is an order of magnitude faster in reaching viable designs. The pipeline is closed-loop, requiring only the initial part file of the mechanism, and the desired features in the part for optimization. With these inputs, the pipeline automatically parameterizes the desired elements, varies them across a range and generates a set of geometrically different designs. These candidate designs are loaded in a multibody dynamics simulation engine, and evaluated against hundreds of operational cases derived from mission requirements; the telemetry generated from the simulations are then evaluated by user defined scoring metrics. The candidate designs' associated scores are used as inputs in a machine learning algorithm, where the resultant output is a new array of parameters, fed back to the CAD generation pipeline. A new set of designs are then generated and the process starts again. This repeats for a number of iterations, and terminates when a superior candidate design emerges - optimally meeting the desired requirements.

The initial findings of this optimization pipeline demonstrate an ability to generate feasible designs in a shorter period of time than the incumbent process. The proof-of-concept pipeline used an initial test-set of intentionally sub-optimal designs for a chosen robotic mechanism on Canadarm3 and, in a fraction of the time and cost, generated a reasonably comparable output to the design made by the RSO team (which had undergone initial prototyping and successful testing). As the pipeline's fidelity improves

and successfully vetted on other mechanisms, it can serve as a tool to rapidly create new possibilities for the design of robotic mechanisms on large-scale missions.