Space Debris Identification and Characterization via Deep Meta-Learning

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ABSTRACT

Space debris identification and characterization is a problem of paramount importance in Space Situational Awareness (SSA). Currently, the Joint Space Operation Center (JSpOC) Mission System (JSM) is tracking more than 29,000 resident space objects greater than 10 centimeter in size. It is estimated that more than 500,000 objects larger than 1 cm are currently orbiting Earth in the LEO/MEO/GEO regime. As a result, new methods are needed to effectively identify, characterize and concurrently track such large number of objects. Recent advancements in deep learning (e.g. Convolutional Neural Networks (CNN), Recurrent Neural networks (RNN)) have shown tremendous results in many practical and theoretical fields (e.g. speech recognition, computer vision, robotics). Whereas deep learning methods are becoming ubiquitous, they have been barely explored in SSA applications, in particular with regard to space debris identification and characterization.

In this paper, we design, test and validate a new class of deep learning algorithms that can discriminate debris from non-debris objects using single and multi-color light curve data. Recently our team demonstrated that deep CNN and recurrent networks, e.g. Long-Short Term Memory (LSTM) networks, trained on real and simulated light curves can be effectively employed in discriminating between active satellites, debris and rocket bodies. However, such algorithms are computationally expensive to train and require a large number of available labeled data. The latter are generally time consuming to obtain. Recently, a new paradigm within the machine learning community emerged, where deep networks are designed with procedures that can teach the system to *"learn-to-learn."* Named *Meta-Learning*, it relies on the assumption that a deep learning system can mimic the ability of humans to efficiently learn to recognize objects from a few examples. Indeed, meta-learning is implemented by defining a learning procedure that can be carried along a distribution of the multiple tasks, each with a limited number of examples. Here, we train deep networks with meta-learning (e.g. Model-Agnostic Meta-Learning, MAML) to show that such class of algorithms can effectively solve the debris/non-debris problem by processing single and multi-color light curves. More specifically, we will employ a combination of simulated and real-data to show that we can train meta-learning-based CNN can efficiently and quickly learn to discriminate debris from non-debris object under a variety of observational conditions. We will test and validate the proposed methodology using real-data collected by our University of Arizona (UA) RAPTORS EO telescopes.