Using Machine Learning to Infer Material Properties of Debris Fragments from X-ray Images in the DebriSat Project

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ABSTRACT

The DebriSat project is a collaboration effort with the NASA Orbital Debris Program Office, the U.S. Space Force Space Systems Command Center, The Aerospace Corporation, and the University of Florida. To date, over 200,000 fragments from this ground-based, hypervelocity impact experiment have been collected, and processing is underway to determine their physical characteristics, such as material, shape, color, characteristic length, and average cross-sectional area. The x-ray process is primarily used to identify the location of the fragments and estimated size for extraction, so that these physical characteristics can be assessed. This paper proposes a machine learning-based approach to characterize materials from x-ray images of debris fragments embedded in soft-catch foam used in the DebriSat project. The novel methodology discussed in this paper will highlight the use of x-ray imagery data to characterize these fragments without extraction or a human-in-the-loop.

Both supervised and unsupervised machine learning techniques are utilized with this approach to infer the physical parameters of the fragments embedded in the soft-catch foam panels used in the impact experiment based on x-ray images of the foam panels. Additionally, 3D reconstructions of the extracted fragments are created with images taken from two different angles using the structure from motion (SfM) method. The characteristic lengths and shape from the 3D reconstruction, alongside the physical characteristics of the debris, are used in the inference of the material type.

To develop and test the approach, a dataset of x-ray images of debris fragments of varying sizes and materials is collected. Supervised learning methods such as convolutional neural networks (CNNs), support vector machines (SVM), decision trees, and random forest classifiers are used due to the high-dimensional feature spaces of the debris and nonlinear decision boundaries for material categorization. Given the limited pre-labeled data of embedded debris materials smaller than 10 mm, unsupervised machine learning techniques such as clustering algorithms and autoencoders are used, in addition to supervised learning methods. The clustering algorithms group similar fragments together based on their physical properties, and autoencoders reduce the dimensionality of the x-ray images and extract relevant features.

The performance of the proposed approach's is analyzed using a range of statistical methods, including confusion matrices, receiver operating characteristic curves, and precision-recall curves. The results are compared with those obtained using a baseline approach that relies on manual identification and classification of debris fragments. To evaluate the effectiveness of different machine learning methods, statistical tests such as t-tests, ANOVA, and cross-validation are performed, comparing the performance of CNNs, SVMs, clustering algorithms, and autoencoders. Additional analysis needs to be conducted to identify any sources of bias or variability that may affect the results, such as variations in imaging conditions or fragmentation patterns. Other topics explored are limitations, refinements, and the potential use of semi-supervised learning techniques, such as self-training to label unlabeled datasets and co-training using x-ray images taken from two different angles as two different models.