Materials Research Proceedings 37 (2023) 499-503 https://doi.org/10.21741/9781644902813-109

Space object identification and correlation through AI-aided light curve feature extraction

Chiara Bertolini[1,a], Riccardo Cipollone[1,b*] , Andrea De Vittori[1,c], Pierluigi Di Lizia[1,d], Mauro Massari[1,e]

[1] Department of Aerospace Science and Technology, Politecnico Di Milano, Via Giuseppe La Masa 54 20156, Milano

[a]chiara.bertolini@polimi.it, [b]riccardo.cipollone@polimi.it, [c]andrea.devittori@polimi.it, [d]pierluigi.dilizia@polimi.it, [e]mauro.massari@polimi.it

Keywords: Light Curves, Neural Networks, Correlation

Abstract. With the constant growth of objects in orbit, the monitoring and cataloging of space population is essential. Light curves obtained from ground stations support this point, providing valuable information about the observed objects. The idea of using them to identify an object through correlation with a catalogued reference takes hold from their wide availability. This article focuses on the development of a tool for the analysis and correlation of two light curves, ARIEL. This tool is built through neural networks and declined in three strategies, each with its own goal: ROGUE, LINDEN and SIERRA. The light curves were retrieved via the database managed by the Mini-MegaTORTORA observatory and filtered using the Savitzky-Golay filter.

Introduction

The near-Earth environment is getting more populated, as commercial applications become a substantial part of the space economy, increasing the risk of collisions and fragmentations [1]. To keep track of this expanding population and to assess the risk of in-orbit collision and fragmentation, space agencies deploy Space Surveillance and Tracking (SST) systems [2]. Ground-based stations allow to retrieve orbital data of human-made objects [3]. When dealing with optical telescopes, photometry analysis can be performed, and light curves are generated as a consequence. Light curves, which represent object brightness variations, provide information on orbit regime, tumbling motion, and spacecraft geometry, enabling characterization of observed objects.

In general, traditional estimation-based methods, like the so-called Light Curve Inversion, have been extensively used for the identification of space objects [4]. However, complex models have to be considered and the resulting analysis is computationally time-consuming. Consequently, the state of the art is now drifting to the use of machine learning with bespoke Convolutional Neural Networks (CNN) or Recursive Neural Networks (RNN) ensuring up to 90% prediction accuracy [5][6].

This project proposes a novel approach to light curve characterization through the Machine Learning based Light curve Analysis (ARIEL) tool. Raw light curves are recovered from the database managed by the Mini-MegaTORTORA (MMT-9) observatory [7] and then pre-processed, before being fed into three different neural networks (NN): ROGUE, LINDEN, and SIERRA.

Performance for these networks is then assessed using different datasets obtained by varying the number of spacecraft platforms.

Theoretical background

As mentioned above, light curves are recovered from shots acquired with optical telescopes. An example of the observatory is represented by MMT-9 system [6], which predisposes a constantly updated database for human-made space objects. From that database, the main information recovered are the space object characteristics and corresponding light curves retrieved, each associated with a track ID and time-tag. The data are summarized in the following Table.

Table 1 – Data recovery from MMT-9 database

Data	Number of objects
Total number of objects recovered	6.314
Total number of light curves available	Over 150.000
Objects per category	
Type of orbit	LEO: 5.206; GEO: 174; Other: 934
Attitude regime	Periodic: 985; Aperiodic: 1550; Non variable: 3779
Type of object	Rocket bodies: 827; Debris: 839; Satellites: 4648

Before entering the NN, however, these raw light curves are pre-processed using the Savitzky-Golay filter [8], with smoothing properties particularly indicated for reducing high frequency noise. The outcome can be seen in Figure 1, where the grey signal is the raw light curve, while the red is the filtered one.

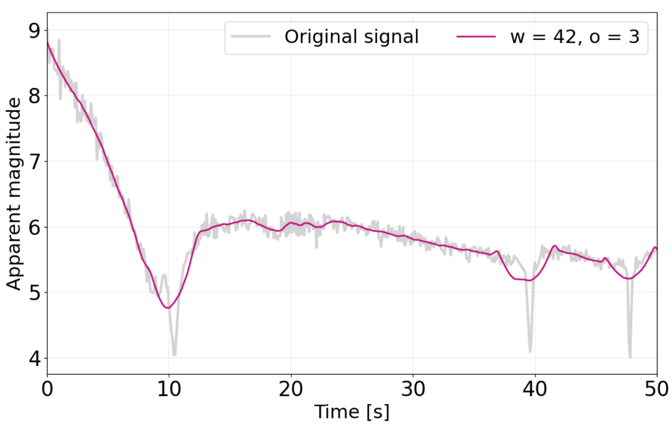

Figure 1 - Filtered light curve (cropped)

To assess the performances of the ARIEL networks, the focus was mainly on objects belonging to LEO or Low-Medium Orbit (LMO) regions, with periodic or aperiodic tumbling motion. The corresponding light curves have been filtered and stored in datasets, accompanied by the name and the type of object considered, i.e. Rocket body, Debris or Satellite. To avoid any bias towards a specific spacecraft, different platforms for each type are considered. For example, a dataset considers light curves belonging to Iridium and NOAA objects, but both labeled as "Satellites" – as stated in the MMT-9 database. Two different sets have therefore been considered. First, the Nominal dataset represent nominal conditions of operation of ARIEL, meaning a limited number of platforms a first version featuring periodic objects only, and a following one including aperiodic too. Then, a Variability test assesses the extent of ARIEL capabilities: different datasets are built considering an increasing number of platforms for each dataset, taking care that the three types data distribution is balanced out. All the objects considered have periodic or aperiodic attitude regime.

Deep learning networks are a subset of Machine learning models. Different NN structures can also be employed such as CNN and RNN: CNNs are particularly indicated to retain the general features of the input, while, RNN, such as the Long-Short Term Memory (LSTM) cells, take into account the input's time-dependence. After the NN setup, it needs to be trained and its performance assessed – mainly in terms of predictions' Accuracy. Particular attention has to be given in the model structure and dataset provided to avoid over- or underfitting of the network.

Siamese networks have a slightly different architecture [8]: the overall dataset is divided in Anchor, the reference, Positive and Negative, the closest and the farthest prediction from the reference. Then, an embedding model extracts features from the inputs and the network evaluates the distance Anchor-Positive and Anchor-Negative in order to bring the former closer and the latter farther. Thus a dedicated metrics, Similarity, is employed.

Architectures

Three different architectures are developed inside the ARIEL framework: ROGUE, LINDEN and SIERRA.

The Rocket bodies Light curves Identification (ROGUE) network aims at recognizing Rocket bodies among light curves of different types. The structure is a combination of CNN and LSTM cells. This test is conceived to verify the capability of the NN to identify a defined category of spacecraft.

The Light curve Identification and Correlation (LINDEN) NN compares two light curves and determines the correlation degree among the twos. Two models have to be therefore developed as shown in Figure 2:

- the Feature extraction part analyses the light curves and predicts the objects' type
- the Correlation evaluation block which, given the above-mentioned predictions, evaluates the distance between them.

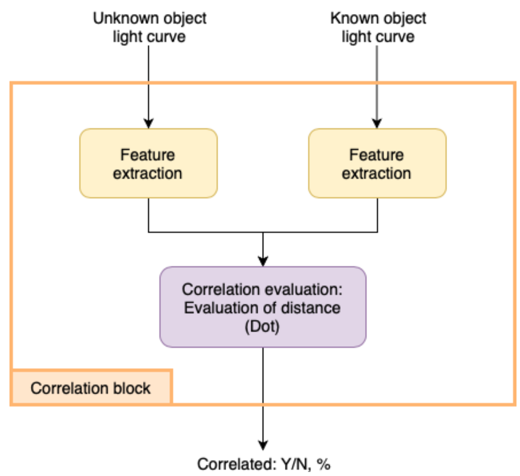

Figure 2 - LINDEN Structure

The Feature extraction model is an improved version of the ROGUE model and the output gives a prediction vector over the class labels.

After having trained the Feature extraction part, it is inserted in the overall LINDEN Correlation block where the correlation between the prediction vectors is performed, thanks to a normalized dot product. As the Feature extraction model is frozen within the Correlation block, this allows to compute a correlation degree without being influenced by uncertainties in the model.

Siamese Network for Light curves Correlation (SIERRA) is a Siamese Network, which encompasses the above-mentioned Feature extraction block as embedding model.

Results

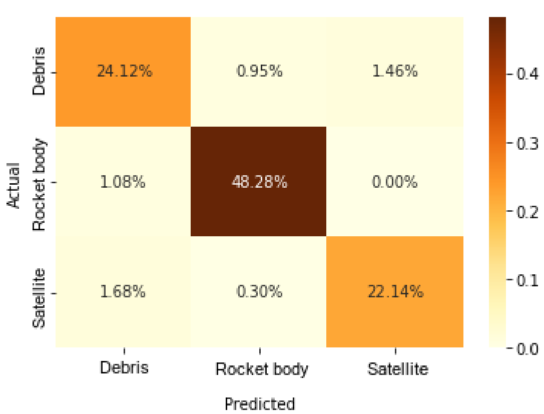

Figure 3 - Confusion matrix for LINDEN Feature extraction

Hereafter the results for ARIEL networks are summarized, obtained considering the above-mentioned datasets. The training has been performed using Google Colaboratory, where due to the limited GPU time availability, it has been divided in sessions from 100 to 200 epochs. The results are analyzed through confusion matrices, which compare predicted with actual labels. The more intense the color of the cell, the higher the prediction accuracy. An example can be shown in Figure 3 – where the results for LINDEN Feature Extraction for the second Nominal dataset are shown.

ROGUE: The results show around 97% accuracy for Nominal datasets while a drop can be observed for Variability sets – ranging from 95% to around 70% accuracy for increasing number of platforms. All in all, ROGUE can best differentiate the Rocket body type among up to 20 different platforms. However Nominal datasets do not present overfitting as Variability sets do.

LINDEN: As previously mentioned, the Feature extraction block is trained separately and then inserted in the overall Correlation block.

Feature extraction block: The results display over 95% accuracy in differentiating the type of objects inputted, for Nominal sets. Variability datasets still reach over 90% accuracy for lower numbers of satellite platforms, while severe overfitting can be noticed with increasing variety, with accuracy dropping down to 50% in the best-performing model. Moreover, the Debris type is completely missing among output predictions, which enforces the idea that they are more difficult to categorize due to their nature.

Correlation block: The performances observed prove that, as the levels reached in the Feature extraction block leave room for uncertainty, the results obtained in the Correlation block are quite scarce, in particular for the Variability datasets. Overfitting is observed also in Nominal conditions becoming even more relevant for the Variability datasets. However, the confusion observed is still below the 10% bound.

All in all, LINDEN proves its capabilities by granting an accurate type recognition, which allows correlation between the two inputs to be established properly. However only up to 20 platforms can be considered at the same time in order to obtain accurate results.

SIERRA: As expected, the overfitting present in the Feature extraction block propagates to the NN. The Similarity obtained in the different datasets is roughly giving a 10 % gap, therefore the Positive and Negative outcomes are properly distinguished. While using the Variability dataset with the lowest number of platforms – around 20 –, a remarkable confusion was observed. This was maybe due to Anchor and Negative having common characteristics not considered during the Feature extraction block.

Conclusions

ARIEL provides a strategy to identify objects according to their type and to establish a degree of correlation between the unknown object and a catalogued one. This is done by the analysis of light curves through a deep learning model combining CNN and LSTM layers that grasp general and time-dependent features at the same time. Three architectures are thus proposed, each focusing on a different aspect of the problem at hand: ROGUE, LINDEN and SIERRA.

The light curves are obtained from the MMT-9 database and have been pre-processed, in particular filtered with the Savitzky-Golay smoothing filter.

After extensive training using different datasets, the performances have been assessed, showcasing a resulting accuracy of around 90% in most test cases. The significant gap observed for the similarity in SIERRA proves these networks predict the type of object with little confusion. However these NN are limited by datasets including diverse platforms, where accurate type recognition is hampered, thus preventing the correlation to be performed. Moreover, overfitting is omnipresent: in some cases it becomes substantial, therefore impacting the accuracy of the predictions done.

Some options can hence be proposed to improve ARIEL, e.g. consider a smaller number of different platforms or restrict the problem to the recognition of platforms among a same type, or a same attitude regime (i.e. periodic, aperiodic or non variable), or even focus on the problem of the Debris type recognition. In fact it is the most mistaken type, as some of these objects are unused satellites or intact rocket body parts. Therefore, a dedicated analysis among Debris may be needed if those objects are involved.

References

[1] ESA Space Debris Office, “ESA annual space environment report,” Tech. Rep. 6, Euro- pean Space Agency, Darmstadt, Germany, April 2022.

[2] EU SST, “European space surveillance and tracking,” 2016. https://www.eusst.eu.

[3] Montaruli, Marco Felice & Facchini, Luca & Di Lizia, Pierluigi & Massari, Mauro & Pupillo, Giuseppe & Bianchi, Germano & Naldi, Giovanni. (2022). Adaptive track estimation on a radar array system for space surveillance. Acta Astronautica. 198. https://doi.org/10.1016/j.actaastro.2022.05.051

[4] B. Bradley and P. Axelrad, "Lightcurve in- version for shape estimation of GEO objects from space-based sensors," ISSFD, 2014.

[5] R. Linares and R. Furfaro, "Space object classification using deep convolutional neural networks," IEEE, 2016.

[6] E. Kerr, G. Falco, N. Maric, D. Petit, P. Talon, E. Geistere Petersen, C. Dorn, S. Eves, N. Sánchez-Ortiz, R. Dominguez Gonzalez, and J. Nomen-Torres, "Light curves for GEO object characterisation," (Darmstadt, Germany), ESA, ESA Space Debris Office, 4 2021. Proc. 8th European Conference on Space Debris.

[7] S. Karpov, E. Katkova, G. Beskin, A. Biryukov, S. Bondar, E. Davydov, E. Ivanov, A. Perkov, and V. Sasyuk, "Massive photometry of low altitude artificial satellites on Mini-Mega Tortora," 2015. Database: http://mmt.favor2.info/satellites

[8] N. Gallagher, "Savitzky-Golay smoothing and differentiation filter," 2020. https://eigenvector.com/wp-content/ uploads/2020/01/SavitzkyGolay.pdf

[9] H. Essam and S. Valdarrama, "Image similarity estimation using a Siamese Network with a Triplet loss," 2021. https://keras. io/examples/vision/siamese_network/