Detection methods for a statistical analysis of the population of satellites and space debris from astronomical images

Elisabeth Rachith
Laboratory of Astrophysics EPFL LASTRO, Observatoire de Sauverny, CH-1290 Versoix
elisabeth.rachith@epfl.ch

Belén Yu Irureta-Goyena
Laboratory of Astrophysics EPFL LASTRO, Observatoire de Sauverny, CH-1290 Versoix
belen.irureta@epfl.ch

Jean-Paul Kneib
Laboratory of Astrophysics EPFL LASTRO, Observatoire de Sauverny, CH-1290 Versoix
jean-paul.kneib@epfl.ch

ABSTRACT

A growing number of satellites and space debris orbit the Earth. This increasing population represents both a danger to space operations and a disruption for astronomical observations by adding unwanted signal on top of the astrophysical data. It is therefore critical to monitor and quantify the population of satellites and space debris to understand and prevent the consequences of their increasing number.

A way to identify satellites and space debris in the visible band is to look at the characteristic streaks of light they leave in astronomical images taken from ground-based telescopes and compare them to existing satellite catalogs. This allows for the assembly of a comprehensive overview of the global satellite and space debris population, as well as for the identification of unlisted resident space objects. Orbital data, as well as satellite and space debris ephemerides, can also be corrected and their accuracy improved when compared with the actual measurements collected. The first step in this direction is to detect the traces left by satellites and space debris on astronomical images and the work presented here evaluates two detection methods.

The first method uses in particular the Hough transform algorithm for the detection of streaks in raw astrophysical images. The input images – raw unstacked astronomical images – are first cleaned of elements that could hinder the detection of satellites and space debris using Gabor filters, a top-hat transform and various thresholding carefully optimized to prevent unwanted detection with the Hough transform while ensuring a minimum of information loss. The elements that need to be removed from the images are bad columns, persistence effects and saturated bands among others, as well as very bright stars that can interfere with the detections. A Canny filtering algorithm is then applied on the images to detect the edges of the streaks left by the satellites and space debris crossing the field of view and a Hough transform algorithm finally differentiates the traces of the other elements of the image.

The second detection method evaluated is based on the adaptation of a machine learning algorithm initially proposed by Lin et al. for line detection in an urban environment. It is composed of a neural network of the LCNN type (Lookup based Convolutional Neural Network) enhanced with a trainable Hough transform prior block. The ability of the algorithm to correctly detect satellite tracks and space debris in astronomical images is evaluated after different training phases and the algorithm is finally applied, as for the detection method using the Hough transform, on a subset of images obtained with the 2.5m VLT Survey Telescope (VST).

The benefits and drawbacks of both methods are presented and discussed and ultimately, using the most accurate and complete method for streak detection and thanks to the sensitivity of VST and its comprehensive archive, we expect to detect more satellites and space debris than predicted by existing catalogs. Our goal is to give a quantitative overview of the impact of light streaks of satellites and space debris on astronomical images as a function of time, thus providing statistical monitoring of the global satellites and space debris situation.

1. INTRODUCTION

"*Space debris are all man made objects including fragments and elements thereof, in Earth orbit or re-entering the atmosphere, that are non functional*"

More than 130 million space objects would correspond to the above definition given by the Inter-Agency Space Debris Coordination Committee (IADC) [1], among which 1'000'000 have a size between 1 cm and 10 cm, 36'000 have a size greater than 10 cm and 32'000 are tracked by space surveillance systems on a daily basis [2].

Space debris, because of their presence in the orbits of functional satellites, represent a significant risk to the safety and survival of the latter. Indeed, due to the high velocities involved, even debris of a few millimeters in size can seriously damage the vital systems of a satellite, while debris larger than one centimeter will mostly lead to its destruction [3] [4].

Old satellites that are no longer functional, rocket bodies that remain in orbit after launches, particles produced during solid combustion in rocket engines [5], and operational debris such as objects lost by astronauts or parts of satellites that detach from the main body during routine operations are all direct sources of space debris creation in the near space environment. In addition, ASAT tests (anti-satellite missions designed to deliberately destroy a space object in orbit) conducted by China, the United States, India and Russia [6], and spontaneous fragmentations or collisions between space objects [7], whether operational or not, also contribute significantly to the increase of the space debris population [4] [8] [9]. Depending on their altitude, the debris remain in orbit for several months, years, centuries or even thousands of years for the most distant ones, implying a disproportionate accumulation of waste material having an impact well after the launch of the payload and the end of its operational life. This raises questions of great importance for the sustainability of our space operations, especially since we are now at a turning point of the space era with a multitude of new national as well as private actors [10] [11], an example being the gigantic satellite constellations that are currently being put in place and, inevitably, will contribute to the creation of new debris [12] [13].

Beyond the operational risks posed by space debris, they also impact astronomical research by leaving characteristic light traces on telescope images that diminish their quality [14], and as the number of debris continues to grow along with the increasing number of new satellites launched, they even seem to impact nighttime luminosity around the globe [15]. It is therefore essential to know precisely the state of our space environment to be able to predict collisions, mitigate the harmful effects of debris, or plan de-orbiting missions. The knowledge of the state of space debris as a function of time is also a necessity for the understanding of the evolution of this population [16]. The formulation of laws and recommendations to minimize their creation and avoid a generalized uncontrollable situation [17] also relies on an accurate knowledge of the global state of the population.

Space debris are studied using radar and optical observations for the largest ones [3] and statistical models for the smallest ones [18] [19]. Several teams carry out regular sky surveys in order to correct, complete or modify the orbital data of known objects as well as to continuously complete the existing databases with the information of newly discovered debris [20] [21] [22] [23] [24] [25]. Existing catalogs include the Discos database by ESA [26], Space-Track, the database of the US space surveillance network [27], Astriagraph by the University of Texas at Austin [28], MMT by the University of Kahzan [29], JSC Vimpel by JSC Vimpel Interstate Corporation in Russia [30] and Celestrack by Dr. T.S. Kelso [31].

Given the need for accurate and precise databases for all SSA activities, this research aims to close the gap between the reality of the space environment and our knowledge of it. The first objective and the one presented here is the detection of space objects, whether they are operating satellites or space debris.

Astronomical research, by its nature and its associated needs, generates huge collections of images of the sky and although the search for space debris is sometimes associated with it, observations of objects of astronomical interest such as galaxies, supernovae and others and observations of debris are often carried out during separate observing sessions dedicated to one or the other domain. However, by having a quick look at the images taken by astrophysicists, it is easy to notice that they are studded with traces of light mainly due to satellites and space debris. These traces are usually simply removed from the raw data without further consideration, and it is in order to use this wealth of information that the present research uses data from wide-field ground-based telescopes whose primary use is astronomical research not dedicated to space debris observation. In this way, it is also possible to take advantage of

the large archives of astrophysical research, allowing in addition to detect and characterize satellites and space debris individually, to draw the evolution of these populations in a global and systematic way.

1.1 Related work

The research work presented in the next chapters is based on studies done by several teams for the detection of traces on astronomical images. The StreakDet framework uses a combination of segmentation and classification, for the detection and identification of traces respectively [32], [33] uses similar methods for real time detection of satellites, other works utilize the well known and widely used Hough or Radon transforms [34] [35] [36] and finally some teams are exploring the use of machine learning for the retrieval of satellite and space debris data from images [37] [38].

2. METHODOLOGY

As previously discussed, the development of the pipeline is initially focused on the detection of light traces in astronomical images and it was decided to focus on two types of methods to compare them and determine their respective effectiveness. Morphological analysis methods on the one hand, which have been used for several decades for the detection of patterns and which have proven their effectiveness and machine learning methods on the other hand, which, although more recent, have allowed great advances in the field of object or pattern recognition in images.

2.1 Hough transform method

The developed algorithm is based on the Hough transform algorithm which allows, by transforming the Cartesian space into a polar coordinate space, to facilitate the detection of shapes in the images, especially straight lines such as of interest here. The images given as input are in raw format without any pre-processing and the first step is to remove bad columns and other defects that could influence the detection negatively. The defects are due to saturated or dead pixels and to the persistence effect, and are removed from the image by masking using different thresholds, Gabor filters and a top-hat transform for the differentiation of the saturated columns from the satellite tracks. Once the major image defects are removed, a Canny filter is applied to detect the contours of the features present, and the result is then passed through the Hough transform for the differentiation of straight lines from other shapes, for example those of stars, galaxies, or other image defects that could not be removed earlier. Finally, the detected lines that may correspond to satellite or space debris tracks are analyzed by comparing the orientations and choosing the line with the highest sum of pixel intensity in the given direction, thus corresponding to the sum of pixel intensity along the original track. A diagram showing the high level functioning of the algorithm can be seen in Fig.1.

The different thresholds and filters have been carefully optimized to obtain the best results for astronomical images while remaining functional for all types of image sources, the long-term intention being to use the algorithm on images from multiple telescopes.

2.2 Machine learning method

The machine learning algorithm used in this work is a convolutional neural network with a trainable Hough transform prior block called HT-LCNN (Hough Transform Lookup based Convolutional Neural Network) developed by Lin et al. [39]. The structure of the neural network is such that the Hough transform block allows the learning of the global features of the image, i.e. the location of the lines to be detected, while the convolutional layers focus on the learning of the local feature. A diagram of the functioning of the Hough transform block can be seen in Fig.2. This block can be integrated in several locations of the code to allow for specific tuning of the global LCNN algorithm.

The algorithm, trained and tested on the Wireframe and York Urban datasets, is initially intended for edge detection in buildings and interior images, and can be used for automatic orientation of smart objects. In order to tune the algorithm to our own situation, namely the detection of traces in astronomical images, it is necessary to create our own dataset for training the neural network and 224 VST (Very Large Telescope Survey Telescope) mosaics, corresponding to 7168 individual images, were therefore annotated and prepared for this purpose. Three methods will be evaluated in the next chapter: the pre-trained algorithm with the weights and biases directly given by the authors, after training on the Wireframe and York Urban datasets, the training of the algorithm on our VST dataset only and finally the training on the VST dataset from the algorithm pre-trained on the Wireframe and York Urban datasets, thus allowing to keep the features already learned by the neural network while fine tuning on the data specific to the case studied.

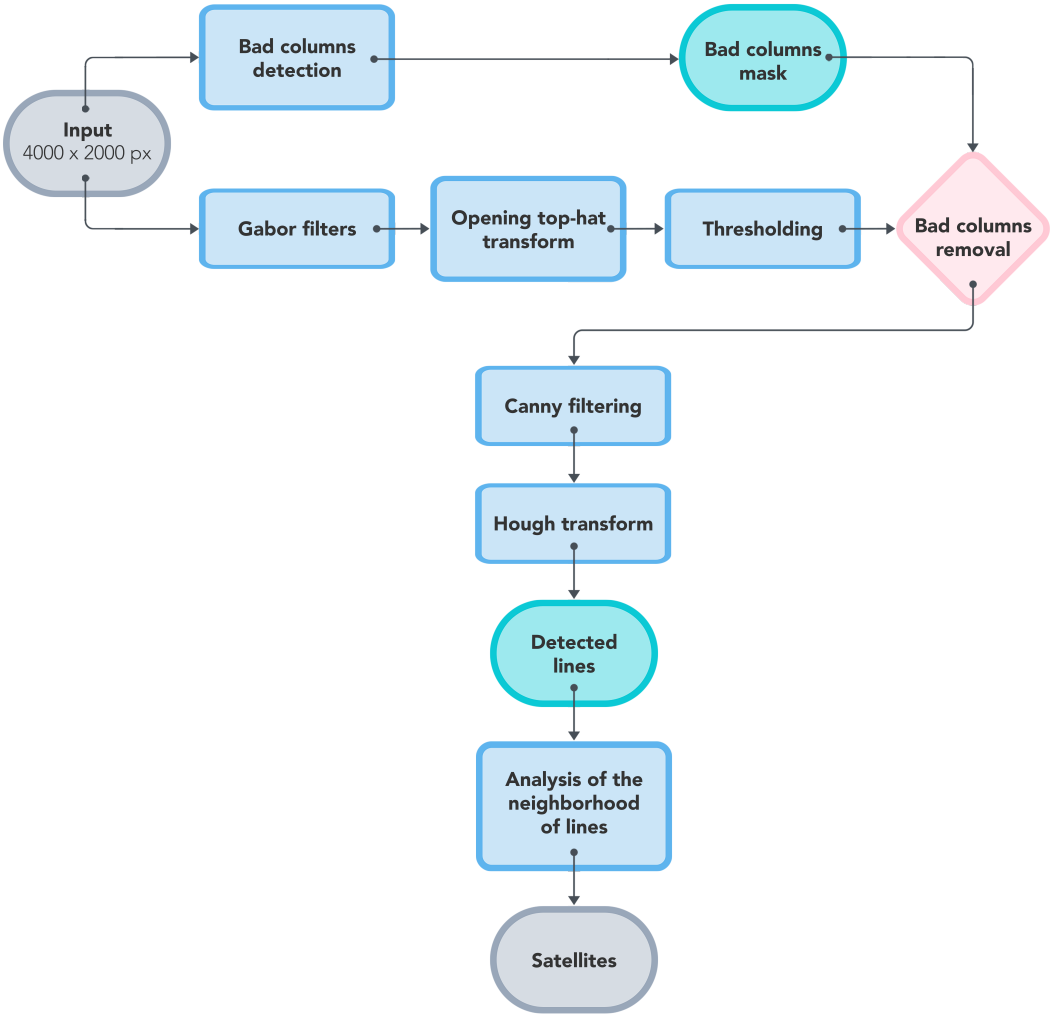

Fig. 1: Flowchart of the Hough transform method. Adapted from Yann Bouquet.

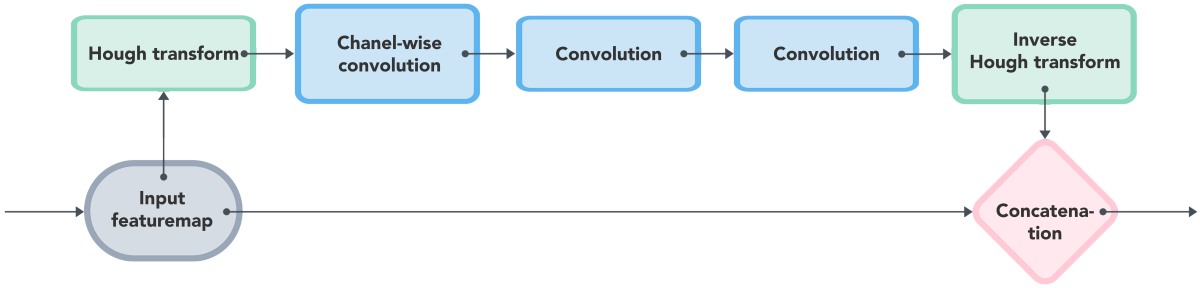

Fig. 2: Flowchart of the Hough transform block in the machine learning method. Adapted from [39].

2.3 Data

In order to test the detection capabilities of the algorithms, they have been tested on the images of the VST, mentioned briefly above, chosen on the one hand for their easy access, the LASTRO having a privileged access for a part of the images and the remainder being public, and on the other hand because the VST possesses an enormous quantity of archived images, corresponding to more than 10 years of regular observations and several hundreds of terabytes of data, allowing an analysis of the evolution of the populations of satellites and space debris over this period. The test set contains 92 mosaics, each containing 32 individual images (of 8MP each) of the night sky. The same test set has been used for the assessment of all the algorithms and the images where not included in the training set of the machine learning algorithms, nor have been used for the tuning of the parameters of the Hough transform method.

3. RESULTS AND DISCUSSION

3.1 Hough transform method

The analysis of the test set using the Hough transform method allowed the detection of 45 objects with up to 4 traces per mosaic. An example of detection can be seen in Figure 3. About 80% of the tracks detected were indeed satellites or space debris, while 20% were found to be false positives, i.e. tracks were detected but turned out not to be satellite or debris marks, while a little more than 10% of the tracks actually present were not detected by the algorithm (false negatives).

Fig. 3: Example of a detection with the Hough transform method.

During this analysis the advantages and drawbacks of the method could clearly be highlighted. Thanks to the relative simplicity of the code, it is possible to understand the impact of each component of the detection system and to modify them independently, allowing a fine adaptation of the process to the type of image analyzed. However, this simplicity also becomes a drawback when the satellite and space debris tracks are too different from each other. Thus, we noticed during the analysis that the most visible traces are almost systematically detected, whereas the traces of lower intensity, having a more diffuse form because of the focus of the image, too short or contaminated by elements of the image which are difficult to remove during the processing, are not detected. An example of this duality is the detection threshold set at 200 pixels in length for a line perceived by the algorithm to be retained as a satellite track. Indeed, a higher threshold would generate too many false negatives, i.e. light traces coming from the passage of a satellite or debris would not be detected, while a lower threshold has shown that many diffraction spikes coming from the brightest stars are too often classified as satellite traces, leading to a large number of false positives. Although the threshold of 200 pixels has been optimized, it does not allow the correct classification of all instances and the algorithm, overall, lacks flexibility and adaptability to the different cases that may be encountered.

Another important element to consider for the qualitative analysis of the algorithm is the processing time. In the case of the Hough transform method, this time amounts to about 15 minutes for the detection of traces in one mosaic, consisting of 32 individual images. This processing time, although it can be reduced by a more efficient rewriting of the code, remains too high since the pipeline developed should in the future be used on the entire VST archive as well as images from other wide-field telescopes.

3.2 Machine learning method

The three versions of our machine learning method have been used on the test set described earlier and some example results can be seen in Fig.4, 5 and 6. The pre-trained model whose weights and biases were provided by the authors [39] following the training on Wireframe and York Urban datasets allowed the detection of almost all satellite and space debris tracks, while having a high number of false positives as can be seen on Fig.4. This behavior is quite understandable given that the algorithm has been trained to detect dozens or even hundreds of lines in a single image and that our images only require the detection of a few lines. The algorithm therefore detects many lines especially on the edges of the image, bad columns and other defects and diffraction peaks of bright stars, while being extremely efficient for the detection of satellite tracks and space debris.

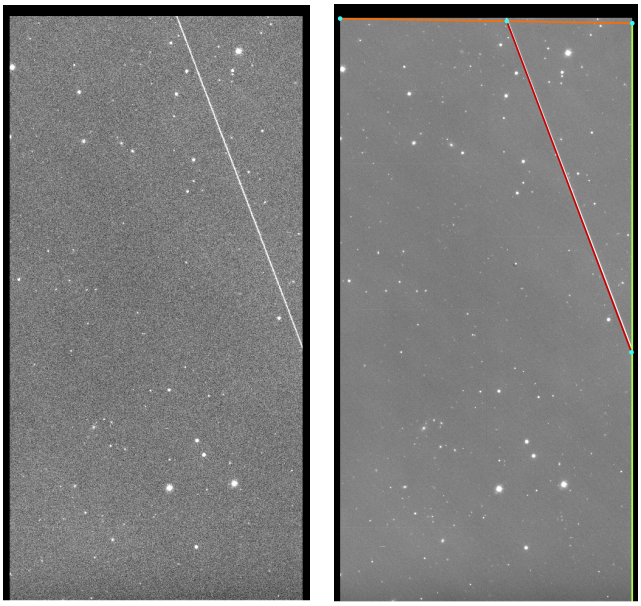

Fig. 4: Example of a detection with the HT-LCNN method, using the pre-trained (on the Wireframe and York Urban datasets) model provided by the authors.

The neural models trained with our own images, exclusively or from the pre-trained model, give instead surprising and rather disappointing results. Indeed, as can be seen in Fig.5 and 6, neither of the two models is able to correctly detect the traces of satellites and space debris and the two lines visible on each of the figures are found identically on all the images tested. Several hypotheses are possible to explain this behavior. First, as explained above, the HT-LCNN algorithm was developed and optimized for the detection of a multitude of tracks in a single image, and both the architecture and the training should be adapted to better take into account the specificities of astronomical images, including the extremely small number of lines per image. Another possibility of improvement could be at the level of the training. Indeed, in order to be as close as possible to reality, the images of the training set have been randomly selected and included independently of the presence of tracks or not, and it would perhaps be judicious to test a training of the model with only images containing tracks. However, care should be taken to ensure that the model is still able to detect no tracks when this is the case and not detect tracks that are not satellites as with the pre-trained model.

The algorithms used required about two days of training on a single GPU, and the time required to process the images with the trained algorithms is about 6 minutes per mosaic, which already represents half the time needed to analyze the images compared to the Hough transform method.

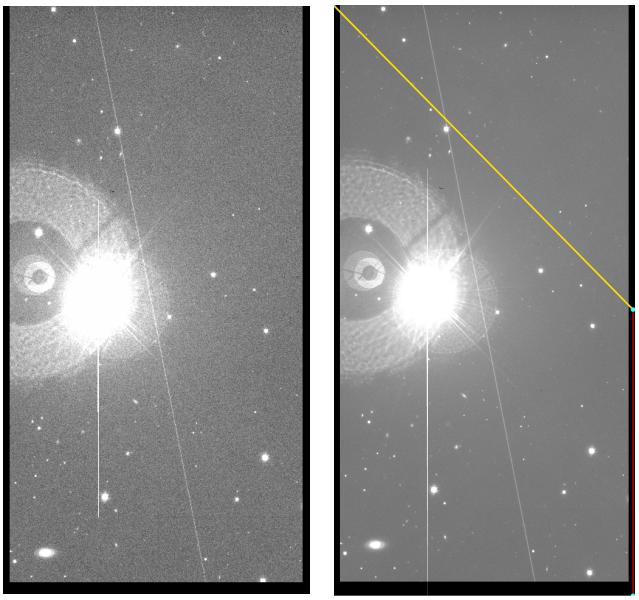

Fig. 5: Example of a detection with the HT-LCNN method, using the model trained exclusively on our dataset.

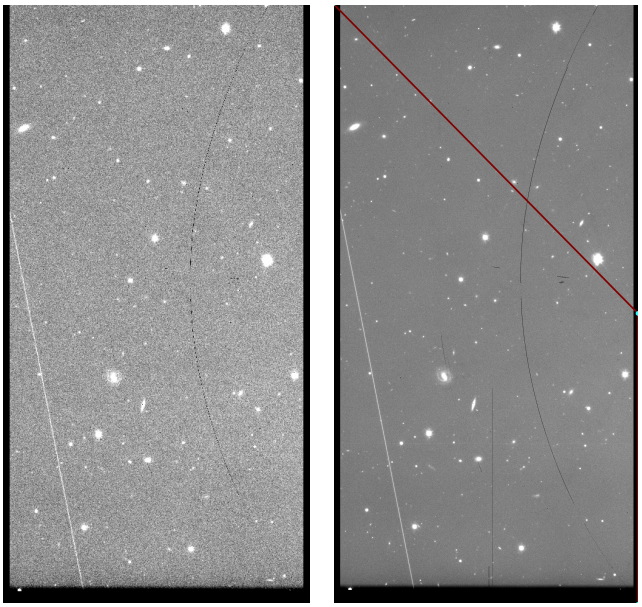

Fig. 6: Example of a detection with the HT-LCNN method, using the model trained on our dataset from the pre-trained model provided by the authors.

4. CONCLUSION

We have seen in the previous chapters that different methods can be used for the detection of satellite and space debris tracks in astronomical images, two of which have been tested in the present work: an algorithm based on the Hough transform and a neural network. The results of the Hough transform method, although relatively good, are not sufficient for a reliable systematic analysis of the space objects present on the astronomical images and in spite of multiple efforts to improve the process, the margin of improvement seems relatively weak. On the other hand, there is no doubt that machine learning techniques are promising, especially for the detection of traces with various shapes and light intensities and in order to discard as precisely as possible the artifacts and other elements of the image that

can disturb the detection. However, they require a particular attention that will have to be reinforced during the next months in order to optimize their use in our research domain. Once the detection of the light streaks is functional, they will be correlated with the existing satellite and space debris catalogs in an automatic way, in order to be able to identify errors in the orbit predictions, missing data or even objects not listed. This collected information can, after verification, be reused in the same catalogs to increase their accuracy and completeness.

We hope to develop an efficient detection pipeline that can be used not only on the VST archive but also on the archives of other wide-field telescopes, all of which contain essential information on the status of satellites and space debris that has been little used so far. The analysis of astronomical images in archives dating back several years will also make it possible to deduce an evolution of the populations of space debris and satellites, making it possible to correlate the collected data with our current knowledge of the close space environment. Statistics related to the location of the telescopes used to take the images will also be made, especially concerning the impact of the traces of satellites and space debris on the capture of images for astronomical research, a subject all the more important as large constellations of satellites are being set up since a few years and the population of space debris does not cease growing.

REFERENCES

[1] Inter-Agency Space Debris Coordination Committee. *IADC Space Debris Mitigation Guidelines*. URL: https://www.unoosa.org/documents/pdf/spacelaw/sd/IADC-2002-01-IADC-Space_Debris-Guidelines-Revision1.pdf (visited on 08/01/2022).

[2] ESA. *Space debris by the numbers*. URL: https://www.esa.int/Space_Safety/Space_Debris/Space_debris_by_the_numbers (visited on 07/27/2022).

[3] J. Silha. *Space Debris – Optical Measurements*. 2020. DOI: 10.1007/978-3-030-38509-5.

[4] A. Murtaza et al. "Orbital Debris Threat for Space Sustainability and Way Forward (Review Article)". In: *IEEE Access* 8 (2020), pp. 61000–61019. ISSN: 2169-3536. DOI: 10.1109/ACCESS.2020.2979505.

[5] M.F. Horstman and M. Mulrooney. "An analysis of the orbital distribution of solid rocket motor slag". In: *Acta Astronautica* 64.2-3 (2009), pp. 230–235. ISSN: 00945765. DOI: 10.1016/j.actaastro.2008.07.015.

[6] J.C. Liou and N.L. Johnson. "Characterization of the cataloged Fengyun-1C fragments and their long-term effect on the LEO environment". In: *Advances in Space Research* 43.9 (2009), pp. 1407–1415. ISSN: 02731177. DOI: 10.1016/j.asr.2009.01.011.

[7] R.S. Jakhu. "Iridium-Cosmos collision and its implications for space operations". In: *Yearbook on Space Policy 2008/2009*. Ed. by K. Schrogl et al. Vienna: Springer Vienna, 2010, pp. 254–275. DOI: 10.1007/978-3-7091-0318-0_10.

[8] ESA Space Debris Office. *ESA'S annual space environment report*. Tech. rep. Darmstadt, Germany: ESA ESOC, 2022.

[9] ESA. *About space debris*. URL: https://www.esa.int/Space_Safety/Space_Debris/About_space_debris (visited on 07/27/2022).

[10] Union of Concerned Scientists. *UCS Satellite Database*. URL: https://www.ucsusa.org/resources/satellite-database (visited on 08/01/2022).

[11] UNITED NATIONS Office for Outer Space Affairs. *Online Index of Objects Launched into Outer Space*. URL: https://www.unoosa.org (visited on 07/27/2022).

[12] J.C. Liou et al. "NASA ODPO's large constellation study". In: *Orbital Debris Quarterly News* 22.3 (2018), pp. 5–8.

[13] S. Le May et al. "Space debris collision probability analysis for proposed global broadband constellations". In: *Acta Astronautica* 151 (2018), pp. 445–455. ISSN: 00945765. DOI: 10.1016/j.actaastro.2018.06.036.

[14] C.G. Bassa, O.R. Hainaut, and D. Galadi-Enriquez. *Analytical simulations of the effect of satellite constellations on optical and near-infrared observations*. 2021.

[15] M. Kocifaj et al. "The proliferation of space objects is a rapidly increasing source of artificial night sky brightness". In: *Monthly Notices of the Royal Astronomical Society: Letters* 504.1 (2021), pp. L40–L44. ISSN: 1745-3925, 1745-3933. DOI: 10.1093/mnrasl/slab030.

[16] V. Braun et al. "Exploiting Orbital Data and Observation Campaigns to Improve Space Debris Models". In: *The Journal of the Astronautical Sciences* 66.2 (2019), pp. 192–209. ISSN: 0021-9142, 2195-0571. DOI: 10.1007/s40295-019-00155-6.

[17] D.J. Kessler et al. "The Kessler Syndrome: Implications to Future Space Operations". In: *Advances in the Astronautical Sciences* 137 (2010), p. 15.

[18] N.L. Johnson. "Space debris modeling at NASA". In: *Proceedings of the Third European Conference on Space Debris, Vols 1 and 2*. Ed. by H. SawayaLacoste. Vol. 473. ESA Special Publications. ESA Publications Division C/O ESTEC, 2001, pp. 259–264. ISBN: 92-9092-733-X.

[19] H. Klinkrad, H. Sdunnus, and J. Bendisch. "Development status of the ESA space debris reference model". In: *Advances in Space Research* 16.11 (1995), pp. 93–102. ISSN: 02731177. DOI: 10.1016/0273-1177(95)98757-F.

[20] C. Zhang and C. Zhao. "Activities of PMO optical space debris survey". In: *Anais da Academia Brasileira de Ciências* 93.suppl 1 (2021). ISSN: 1678-2690, 0001-3765. DOI: 10.1590/0001-3765202120200827.

[21] I.E. Molotov et al. "Search and study of the space debris and asteroids within ISON project". In: *Anais da Academia Brasileira de Ciências* 93.suppl 1 (2021). ISSN: 1678-2690, 0001-3765. DOI: 10.1590/0001-3765202120200145.

[22] F.J. Masci et al. "The Zwicky Transient Facility: Data Processing, Products, and Archive". In: *Publications of the Astronomical Society of the Pacific* 131.995 (2019). ISSN: 0004-6280, 1538-3873. DOI: 10.1088/1538-3873/aae8ac.

[23] J. Silha et al. "An optical survey for space debris on highly eccentric and inclined MEO orbits". In: *Advances in Space Research* 59.1 (2017), pp. 181–192. ISSN: 02731177. DOI: 10.1016/j.asr.2016.08.027.

[24] K.J. Abercromby et al. *Michigan Orbital DEbris Survey Telescope Observations of the Geosynchronous Orbital Debris Environment*. Tech. rep. Houston, USA: NASA, 2011, p. 48.

[25] T. Schildknecht, U. Hugentobler, and A. Verdun. "Optical observations of space debris with the Zimmerwald 1-meter telescope". In: *Advances in Space Research* 19.2 (1997), pp. 221–228. ISSN: 02731177. DOI: 10.1016/S0273-1177(97)00004-5.

[26] ESA. *DISCOS (Database and Information System Characterising Objects in Space)*. URL: https://discosweb.esoc.esa.int (visited on 08/01/2022).

[27] US Space Surveillance Network. *Space-Track*. URL: https://www.space-track.org (visited on 08/01/2022).

[28] University of Texas at Austin. *AstriaGraph*. URL: http://astria.tacc.utexas.edu/AstriaGraph/ (visited on 08/01/2022).

[29] Kazan Federal University. *Satellites identified in MMT data*. URL: http://mmt.favor2.info/satellites (visited on 08/01/2022).

[30] JSC Vimpel Interstate Corporation. *JSC Vimpel - data portal*. URL: http://spacedata.vimpel.ru (visited on 08/01/2022).

[31] T. S. Kelso. *CelesTrack*. URL: https://celestrak.org (visited on 08/01/2022).

[32] J. Virtanen et al. "Streak detection and analysis pipeline for space-debris optical images". In: *Advances in Space Research* 57.8 (2016), pp. 1607–1623. ISSN: 02731177. DOI: 10.1016/j.asr.2015.09.024.

[33] R. Sun et al. "Algorithms for surveying and cataloguing space debris utilizing a wide field of view telescope". In: *Publications of the Astronomical Society of Japan* 71.4 (2019), p. 67. ISSN: 0004-6264, 2053-051X. DOI: 10.1093/pasj/psz046.

[34] P. Hickson. "A fast algorithm for the detection of faint orbital debris tracks in optical images". In: *Advances in Space Research* 62.11 (2018), pp. 3078–3085. ISSN: 02731177. DOI: 10.1016/j.asr.2018.08.039.

[35] T.P.G. Wijnen et al. "Using all-sky optical observations for automated orbit determination and prediction for satellites in Low Earth Orbit". In: *arXiv:2004.08137 [astro-ph]* (2020).

[36] B. Vandame. "Fast Hough Transform for Robust Detection of Satellite Tracks". In: *Mining the Sky*. Ed. by A.J. Banday, S. Zaroubi, and M. Bartelmann. Series Title: ESO ASTROPHYSICS SYMPOSIA. Berlin/Heidelberg: Springer-Verlag, 2001, pp. 595–597. ISBN: 978-3-540-42468-0. DOI: 10.1007/10849171_78.

[37] B. Coelho et al. *New SST Optical Sensor of Pampilhosa da Serra: studies on image processing algorithms and multi-filter characterization of Space Debris*. 2021.

[38] M. Paillassa, E. Bertin, and H. Bouy. "MAXIMASK and MAXITRACK: Two new tools for identifying contaminants in astronomical images using convolutional neural networks". In: *Astronomy & Astrophysics* 634 (2020), A48. ISSN: 0004-6361, 1432-0746. DOI: 10.1051/0004-6361/201936345.

[39] Y. Lin, S. L. Pintea, and J. C. van Gemert. *Deep Hough-Transform Line Priors*. Tech. rep. arXiv, 2020. URL: http://arxiv.org/abs/2007.09493.