Impact of Satellites Streaks for Observational Astronomy: A Study on Data Captured During One Year from Luxembourg Greater Region

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Abstract: The visible and significant presence of satellites in the night sky has an impact on astronomy and astrophotography activities for both amateurs and professionals, by perturbing observations sessions with undesired streaks in captured images, and the number of spacecrafts orbiting the Earth is expected to increase steadily in the coming years. In this article, we test an existing method and we propose a dedicated approach based on eXplainable Artificial Intelligence to detect streaks in astronomical data captured between March 2022 and February 2023 with a smart telescope in the Greater Luxembourg Region. To speed up the calculation, we also propose a detection approach based on Generative Adversarial Networks.

1 INTRODUCTION

We live in a time when global connectivity is becoming an unstoppable trend, with mega satellite constellations such as SpaceX's Starlink, OneWeb and Amazon's Project Kuiper proliferating in low-Earth orbit (Langston and Taylor, 2024). While these satellite networks have started to revolutionize the industry, they also raise growing concerns, for multiple aspects (environment, defence, culture, etc.) (Venkatesan et al., 2020). In particular, the impact of these mega-constellations on astronomy and astrophotography has become a hot topic (Walker et al., 2020), calling into question the possibility of observing the night sky without disturbance.

A modern obstacle is satellite light pollution, which occurs when orbiting satellites reflect the sun's light unto the Earth. This light disturbance can make astronomical observations considerably more difficult (Lawler, 2023), and affect the quality of images captured by amateur and professional astronomers alike:

- Light trails: mega-constellation satellites can create light trails as they pass in front of a telescope or camera lens during long exposure photography. These streaks can compromise image quality by leaving unwanted lines of light across astronomical images.
- Increased sky brightness: the sun's reflection off satellite surfaces can contribute to a general increase in the brightness of the night sky. This makes it more difficult to observe and capture faint, distant celestial objects, such as galaxies, nebulae and faint stars.
- Reduced contrast: the presence of moving satellites can reduce the contrast between celestial objects and the sky background. Subtle details in astronomical pictures, which depend on a dark, uniform night sky, can be compromised by bright streaks and scattered spots.
- Complications for image calibration: satellite light trails can disrupt the process by introducing non-stellar elements into the images, making treatment difficult or even impossible.
- Need for advanced post-processing: this may require technical adjustments and specialized software to mitigate undesirable effects caused by satellites, such as *inpainting*.

It's also a problem for professional ground-based observatories (Hainaut and Williams, 2020), making it imperative to set up a process to estimate concrete impact on the quality of large digital sky surveys (Lu, 2024), avoid disturbances and then correct data if possible (Tyson et al., 2020). The effect is significant: as recent studies have shown (Lawler, 2023; Barentine et al., 2023), the increase in traffic in low-Earth orbit will inevitably lead to a loss of astronomical data and therefore reduce the possibilities of discoveries on the ground, as weak astrophysical signals are increasingly lost in the noise. The International As-

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tronomical Union (IAU) recently published a *'Call to Protect the Dark and Quiet Sky from Harmful Interference by Satellite Constellations'* [1]. Furthermore, it's a hot topic for space-based observatories like Hubble (Kruk et al., 2023), which adds a number of constraints that are difficult to resolve, especially given the cost of operating such facilities in space.

In this article, we propose the study of a dataset made up of astronomical images captured over a year with a smart telescope, in conditions accessible to amateurs, and we evaluate the quantity of images effectively impacted by satellite trails. The rest of the paper is structured as follows. In Section 2, we present a brief review of the state of the art concerning the detection of satellite streaks in astronomical images. Section 3 describes the dataset of images captured by the author, while Section 4 proposes a study of this dataset using different methods. In Section 5, we discuss the results, before concluding and proposing some perspectives in Section 6.

2 RELATED WORKS

For many years now, the scientific community has proposed many techniques to detect and track satellites, and to deal with the trails they cause in astronomical images (Nir et al., 2018; Calvi et al., 2021; Jiang et al., 2023). Specific software for astronomical images processing propose features to manage this problem, like SharpCap [2]. It is important to note that all types of fast-moving Near-Earth Objects, such as meteors, satellites or even cosmic rays, can leave streaks, trails and linear features on astronomical images (Nir et al., 2018).

In the Python software ecosystem, we can mention these tools:

- ASTRiDE aims to detect streaks in astronomical images (Kim, 2016) with boundary-tracing and morphological parameters. ASTRiDE can detect not only long streaks, but also relatively faint, short or curved ones. As we will see later in this article, this is also a problem because it tends to confuse real streaks with tracking problems – so it requires a fine configuration like in (Duarte et al., 2023).
- Authors of (Danarianto et al., 2022) proposed a Python pipeline for lightweight streak detection, identification and initial orbit determination from FITS raw files captured by amateur-grade telescopes – but it was tested on only a few images captured around the celestial equator (85). FITS (Flexible Image Transport System) is a file format most commonly used into store astronomical data.
- A research team applied the probabilistic Hough transform through a Python scripts using well-known open source libraries like openCV and scikit-images, and by using GPU-specific computation to detect streaks in FITS files captured by the Tomo-e Gozen camera at Kiso Observatory in Japan (Cegarra Polo et al., 2021). Unfortunately, the source code is not available.
- pyradon is a Python package based on Fast Radon Transform (FRT) to find streaks in 2D astronomical images (Nir et al., 2018).

Some existing approaches are based on Deep Learning. For instance, an approach based on YOLO (*You Only Look Once*) was proposed by (Varela et al., 2019) to detect streaks in images captured by a multi-camera wide field of view system. The authors note that the labelling of training dataset is an issue. Furthermore, a recent work compared two techniques based on Deep Convolutional Neural Networks: an extended feature pyramid network (EFPN) with faster region-based CNNs (Faster R-CNN) and a feature pyramid network (FPN) with Faster R-CNN (Elhakiem et al., 2023). This approach is elaborated but it was only tested on synthetic data.

In this paper, we compare an existing approach with a dedicated technique combining Deep Learning and eXplainable Artificial Intelligence to search for streaks in astronomical data that we have captured ourselves using smart telescopes.

3 DATA ACQUISITION

Nowadays, Electronically Assisted Astronomy (EAA) is increasingly applied by astronomers to observe Deep Sky Objects (DSO), i.e. astronomical objects that are not individual stars or Solar System objects, like nebulae, galaxies or clusters. By capturing images directly from a camera coupled to a telescope and applying lightweight image processing, EAA allows to generate and display enhanced images on screens (laptop, tablet, smartphone), even in places heavily impacted by light pollution and poor weather conditions. The recent years brought the emergence of smart telescopes, making sky observation more accessible (Parisot et al., 2022). Even the scientific community is taking advantage of these instruments to study astronomical events (i.e. asteroids occultations, exoplanets transits, eclipses) .

In this context, MILAN Sky Survey is a set of raw images with DSO visible from the Northern Hemi-

[1] https://cps.iau.org/documents/49/techdoc102.pdf

[2] https://www.sharpcap.co.uk

sphere (galaxies, stars clusters, nebulae, etc.), collected during 205 observation sessions (Parisot et al., 2023). These images were captured between March 2022 and February 2023 from Luxembourg Greater Region by using the built-in alignment and stacking features of a Stellina smart telescope, based on an Extra Low Dispersion doublet with an aperture of 80 mm and a focal length of 400 mm (focal ratio of f/5), and equipped with a Sony IMX178 CMOS sensor with a resolution of 6.4 million pixels. A CLS filter (City Light Suppression) is placed in front of the camera sensor. The Dawes Limit of the instrument is 1.45 arc-seconds.

The dataset and the data acquisition process is deeply is described in (Parisot et al., 2023), here is a short summary:

- The default settings of Stellina were applied, i.e. 10 seconds of exposure time and 20 dB of gain for each single image. These values are a satisfying trade-off to obtain good images with the alt-azimuth motorized mounts of the instruments (higher value of exposure time may cause a reduction in captured image quality, particularly with *moving blur* (Loke, 2017), higher gain may increase the noise level).
- For each observation session, the instrument was installed in a dark environment (no direct light) and properly balanced using a bubble level on a stable floor (it's mandatory to ensure a good tracking).
- Observation sessions were conducted only when the sky was clear and of reasonable quality. The authors were always present during observations to deal with any weather-related issues such as wind, cloud, fog, rain, or disturbance from animals.

In total, 205 observation sessions, leading to 50068 FITS images of resolutions 3096×2080 were obtained (corresponding to a field of view of approximately $1° \times 0.7°$). As each image was obtained with an exposure time of 10 seconds, it represents a total cumulative time of 139 hours, 4 minutes and 40 seconds.

4 METHOD

We have analyzed the MILAN Sky Survey dataset with different methods, to count FITS files containing streaks, and so the maximum of images impacted by satellites. The computations were realized with the following hardware: 40 cores and 128 GB RAM (Intel(R) Xeon(R) Silver 4210 CPU @ 2.20GHz) and NVIDIA Tesla V100-PCIE-32GB.

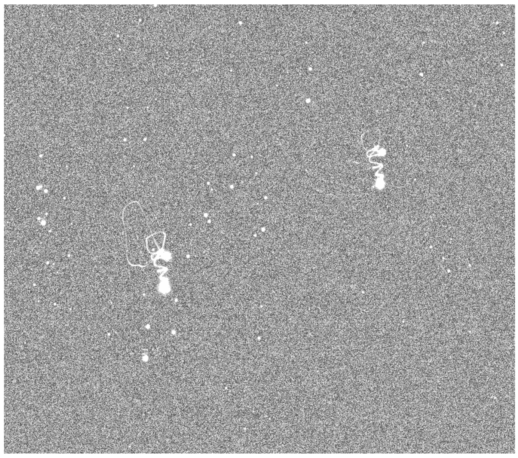

Figure 1: False positive example of streak, due to tracking error. The FITS file is stored in *NGC457-20220807.zip*.

4.1 Detection with ASTRiDE

First, we have tested ASTRiDE, by using different settings and by filtering the results (Table 1). ASTRiDE first pre-processes the image by removing the background using its level and standard deviation before searching for streaks (Kim, 2016). It then computes the contour map to identify all object borders within the image. ASTRiDE then analyzes the morphologies of each object, as determined by the morphological parameters, to differentiate between streaks and stars.

By using the default parameters (*contour threshold*=3, *shape cut*=0.2), and by considering FITS images with at least one detected streak, we observed this selection is too large, retaining images with just blurred stars due to tracking errors (example: Figure 1).

To make a more restrictive selection, we have filtered FITS images with at least one streak with a minimal perimeter (128 pixels), and we have found that streaks are detected in 1316 FITS files for a total of 50068 files, i.e. 2.6 %. In other words, it detected than 137 observation sessions are impacted for a total of 205, i.e. 66 % (Figure 2.

With the standard settings of ASTRiDE, the selection is too large. Moreover, and given the fact that FITS files have an high resolution, the computation may be slow (the tools does not use GPU to speed-up the analysis – the ASTRiDE' authors advice is to deal with parameters to find a good trade-off between accuracy and speed).

So we have tried with optimized settings which

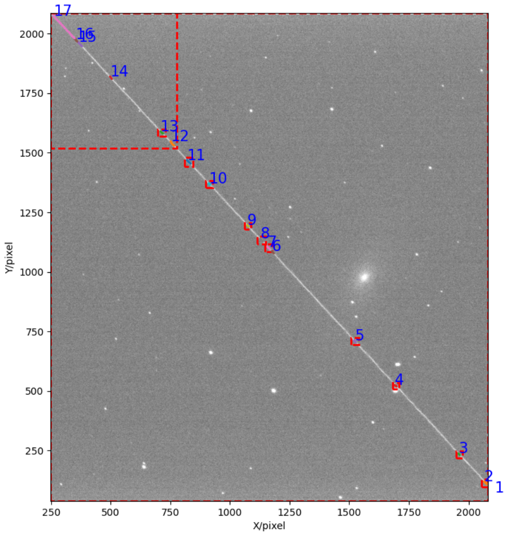

Figure 2: Graphical output of ASTRiDE, after the detection of a large streak in a FITS file captured during an observation session of the Messier 81 galaxy (stored in *M81-20220308.zip*).

are proposed by ASTRiDE authors on the official source code repository (Kim, 2016): by increasing *contour threshold* and by reducing *shape cut*, we avoided selecting FITS files that are impacted by minor tracking errors. Nevertheless, the selection was still too large.

One of the advantage of ASTRiDE is its ability of detecting faint streaks, allowing to detect images damaged by bad tracking (wind, unexpected movement of telescopes, etc.). For this use-case, and keeping into account that our FITS raw images are noisy and far from perfect (especially due to tracking problems), this tool is too sensitive and it is difficult to find the configuration that leads to the detection of streaks produced by satellites by ignoring other issues (Figure 1).

4.2 Detection with a Dedicated ResNet50 Classifier and XRAI

We trained a dedicated classifier to detect images with real streaks – and ignoring defects due to tracking. As we have seen in the previous sections, there are many tools available for this task, the aim is not to re-invent the wheel. Our aim here is rather to have a model that is fully compatible with our input data and its specific characteristics (in particular the fact that it is raw, unfiltered and not debayered).

To this end, we used ASTRiDE to filter FITS images without any streak and/or defect, as ASTRiDE is a sensible and efficient tool for this task. Starting from these images, we generated a dataset with synthetic streaks to train and evaluate a binary classifier. In practice, here are the steps followed:

- From the raw data described in Section 3, we built a set of 25070 RGB images with 224x224 pixels – cutting FITS images into patches to get a resolution that fits to ResNet50 models.
- For each image, we applied a basic stretch to adjust the brightness and contrast to bring out details and make faint structures more visible.
- Random synthetic streaks have been added on half of the images, then we formed two distinct groups, so as to associate a class with each image: images with and images without streaks (we made sure that each group was balanced – to have a classifier with good recall). These streaks were generated by drawing random lines, with different thickness, sizes and color intensity.
- We made 3 sets: training, validation and test (80%, 10%, 10%).
- A dedicated Python prototype was developed to train a ResNet50 model to learn this binary classification. The basic image processing tasks were

Table 1: Experiments with ASTRiDE to detect streaks in FITS images of MILAN Sky Survey. Different settings for ASTRiDE have been tested and compared.

Settings	Filter	FIST Files with detected streaks	Observation sessions impacted
Default (*contour threshold*=3, *shape cut*=0.2)	At least one streak	8704/50068	198/205
Default (*contour threshold*=3, *shape cut*=0.2)	At least one streak with perimeter higher than 128 pixels	1316/50068	137/205
Optimized (*contour threshold*=5, *shape cut*=0.1)	At least one streak	903/50068	101/205
Optimized (*contour threshold*=5, *shape cut*=0.1)	At least one streak with perimeter higher than 128 pixels	404/50068	82/205

performed following best practices for optimizing CPU/GPU usage (Castro et al., 2023).

- Empirically, the following hyper-parameters were used for training: ADAM optimizer, learning rate of 0.001, 50 epochs, 32 images per batch. We thus obtained a ResNet50 model with an accuracy of 97% on the validation dataset. Note that other architectures were also tested (such as VGG16 and MobileNetV2), but the results here are largely similar.
- At the end, we obtained a model with a precision of 0.940, a recall of 0.805 and then a F1-score of 0.867 (Table 2).

Inspired by recent works in the industrial (Roth et al., 2022) and health domains (Chaddad et al., 2023), and to check the robustness of the trained Resnet50 model, we analysed the output with XRAI (*Region-based Image Attribution*) (Kapishnikov et al., 2019). Frequently used in eXplainable Artificial Intelligence for Computer Vision tasks, XRAI is an incremental method that progressively builds the attribution scores of regions (i.e. the regions of the image that are most important for classification). XRAI is built upon Integrated Gradients (IG) (Sundararajan et al., 2017) which uses a baseline (i.e. an image) to create the attribution map. The baseline choice is application-dependent, and in our case we operate under the assumption that a black one is appropriated because it corresponds to the sky background, and the attribution maps is calculated according to the XRAI integration path and reduces the attribution scores given to black pixels. In practice, we used the Python package *saliency* [3] and analysed the output of the last convolution layer. To generate a heatmap indicating the attribution regions with the greatest predictive power, we keep only a percentage of the highest XRAI attribution scores here (for instance, 10 %).

With this pipeline, we have found that streaks are detected in 25 FITS files for a total of 50068 files, i.e. less than 0.05 %; it detected than 18 observation sessions are impacted for a total of 205, i.e. 0.1 %. In this case, we visually noted with the heatmap that the streaks are not caused by tracking problems, but by objects passing through the instrument's field of view during observation, and very probably by satellites. For example, we can mention the following files present in (Parisot et al., 2023): image 44 in *Barnard142-143-20220922.zip*, image 22 in *M17-20220723.zip*, image 40 in *M57-20220602.zip*, image 87 in *M65-20220426.zip*, image 40 in *M103-20220808.zip*, image 167 in *M10-20220615.zip*.

[3] https://pypi.org/project/saliency/

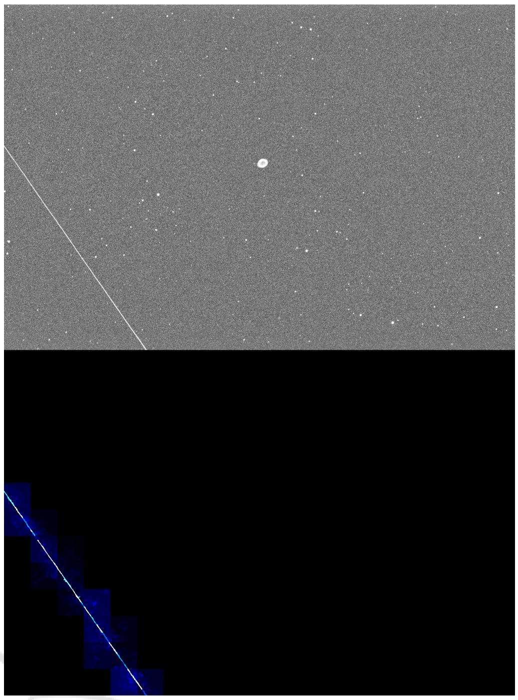

Figure 3: At the top, a stretched 10-second frame of Messier 57. At the bottom, the XRAI heatmap highlighting the pixels that are considered by the Resnet50 classifier for detecting the presence of streaks, by keeping 10% of the highest XRAI attribution scores.

4.3 Fast Approximation with a Pix2Pix Model

Computing a heatmap with XRAI comes at a cost: it requires more computational time and resources than a simple inference of the ResNet50 model. If we consider the analysis of a 3584×3584 astronomical image: with no overlap, it may be necessary to evaluate the ResNet50 prediction and the XRAI *heatmap*

Table 2: Confusion matrix with results of the Resnet50 model on test set (i.e. set of images with synthetic streaks that were randomly added).

	Synthetic streak(s) detected: NO	Synthetic streak(s) detected: YES
FITS images without synthetic streak(s)	1886	103
FITS images with synthetic streak(s)	393	1619

for 256 patches of 224×224 pixels – this may take some time depending on the hardware. To minimise the number of calculations required, we can apply two simple strategies:

- Reduce the size of the image to decrease the number of patches to be evaluated.
- Process only a relevant subset of patches – for example, ignoring those for which the ResNet50 classifier detects nothing.

An other solution consists in estimating the XRAI heatmap with Generative Adversarial Networks (GAN), a class of Deep Learning frameworks that are frequently applied for Computer Vision tasks. A GAN is composed of two Deep Learning models: a generator that ingests an image as input and provides another image as output, and a discriminator which guides the generator during the training by distinguishing real and generated images. Both are trained together through a supervised process – with the goal to obtain a generator that produces realistic images. Among the numerous existing GAN architectures, we selected Pix2Pix – a conditional adversarial approach that was designed for image to image translation (Isola et al., 2017), and applied in many use-cases such as image colouration and enhancement (KumarSingh et al., 2023).

Thus, a Pix2Pix model has been designed to learn the transformation from images with synthetic streaks (like in Section 4.2) and images with the same synthetic streaks but with an other color. We applied the standard Pix2Pix architecture as described and implemented with Tensorflow [4], taking input images of 256 $\times$ 256 pixels, with the same resolution for outputs. The loss function was based on the Peak Signal-to-Noise Ratio (PSNR), and we trained the model during 100 epochs, the batch size was set to 1, and the process was realized with a learning rate of 0.0001. To improve the training phase, as described in (Tran et al., 2021), we applied random data augmentation during each epoch with the imgaug Python package (Jung, 2019).

It led to a Pix2Pix model with a good PSNR (higher that 38.5) – able to reproduce an annotated image (Figure 4), similar to what can be obtained with ResNet50 and the XRAI heatmap. We simply note that this model is slightly more sensitive to noise, especially if it is grouped in zones (and this can sometimes happen with *hot pixels* (O'Brien, 2023)).

In terms of performances, running an inference with the Pix2Pix model on a patch of 256×256 pixels is a better alternative to calculating a heatmap with

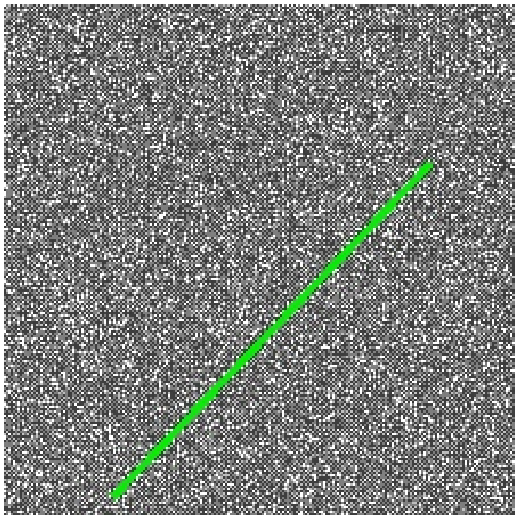

Figure 4: Example of 256x256 patch generated with a Pix2Pix model – with highlighted streaks.

XRAI on a patch of 224×224 pixels: for example, execution time is halved on a laptop without a GPU.

In practice, we used this Pix2Px model to visually check the results obtained in the previous section, by generating and then viewing the output of each image in which a streak was detected.

5 DISCUSSIONS

As it is infeasible to check several tens of thousands of raw images manually, we used different automated methods to filter potentially affected images. It is possible that certain cases have not been identified, in particular when obstacles in the image, tracking problems and streaks can be found in the same images.

Furthermore, the different approaches were tested on images obtained with specific equipment (aperture of 80mm, focal length of 400mm, recent CMOS sensors, alt-azimuth mount) and imperfect conditions. They can therefore be applied to images obtained with identical equipment or with similar characteristics (i.e. other models of smart telescopes with similar technical characteristics). Conversely, applying these techniques on images obtained with smaller or larger focal length instruments would require constituting a dataset that would contain this type of data, to then re-train models.

[4] https://github.com/affinelayer/pix2pix-tensorflow

6 CONCLUSION AND PERSPECTIVES

This paper presents various approaches based on Deep Learning to detect streaks from astronomical images captured with smart telescopes from Luxembourg Greater Region, which required collecting data for over 188 different targets visible from the Northern Hemisphere, with equipment accessible to amateurs.

One approach consists in using ASTRiDE, and this tool is efficient to detect images without streak. The second one is a pipeline combining a ResNet50 binary classifier and the XRAI method, allowing the detection of real streaks with a good accuracy. The last one is an experimental model based on Generative AI in order to highlight the pixels corresponding to the detected streaks.

As a result, we observed that less of 0.05 percent of the captured raw images are damaged by streaks, potentially caused by satellites. In this case it's not much, not enough to require special treatment to fix the affected raw files, a simple filter here may be enough to ignore them after detection.

In future work, we plan to reproduce and improve the current tests on recent and future observations, we plan to gather additional astronomical data (especially from the South Hemisphere), and we will work on optimizations to embed the presented Deep Learning approaches into low resource devices.

Data Availability: The MILAN Sky Survey can be accessed by following the links listed in (Parisot et al., 2023). Additional materials used to support the findings of this study may be available from the corresponding author upon request.

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