

Atmospheric effects on testing and calibrating star tracking algorithms

Louis Jannin
ISAE-SUPAERO
Toulouse, France
louis.jannin@student.isae-superaero.fr

Leonard Felicetti
Cranfield University
Cranfield, United-Kingdom
Leonard.Felicetti@cranfield.ac.uk

Abstract—Star trackers are usually considered to be the most accurate sensors, able to achieve a sub-arcminute precision. Star tracker algorithms are often tested and validated with simulated space views. Testing the algorithms with real space images is expensive as it requires implementing them on existing in-space star trackers, or launching new satellites. This study shows that those algorithms are usually performing poorly with ground-based sky pictures and that some adaptations are necessary to take into account the atmospheric effects. In order to tackle this issue, this study will start by implementing and testing two published Lost-In-Space algorithms with a simulated sensor to compare their performance against various noise sources. After comparing the space-based generated views with ground-based images, an adaptation for the aforementioned algorithms is proposed. In order to counter the effect of atmospheric extinction, the number of stars visible in the image is increased by modifying the field-of-view of the camera, the exposure time and estimating the experimental inter-star angular distance error. The idea is to match the star density used in the state-of-the-art algorithms in the experimental pictures. The modified algorithms are tested with the experimental images, and the adaptation process is validated with a good success rate.

Index Terms—Star tracker, Lost-In-Space algorithms, Multi-Poles algorithm, Polestar algorithm

I. INTRODUCTION

As in-space testing of star trackers is usually very expensive, simulations are often used to test star identification algorithms [1]–[3]. However, the difference in observation conditions and hardware between space and ground severely constrains the requirements of the star identification algorithms, if used on ground-based images. Because of the poor performance of the algorithms with those pictures, some adaptations are necessary to take into account the atmospheric effects and enable the ground testing of such algorithms.

The objective of this study is to survey and quantify those differences, and propose a testing procedure to adapt two state-of-the-art algorithms for star identification with experimental ground-based images taken with a commercial camera. The motivation for such study is two-fold. First, the proposed methodology enables the fast testing of star tracking algorithm prototypes with a full acquisition pipeline, without the need to buy specific testing hardware [4], [5]. Moreover, the same procedure can be applied to many ground-based or air-borne applications that require an accurate star tracking, with low-cost hardware. Possible applications are precise calibration of

backyard telescopes [6], low-cost attitude sensor for atmospheric balloon [7] or precise pointing of optical instruments used for object surveillance and space awareness from ground [8], [9].

The Lost-In-Space (LIS) algorithms are a class of star tracker algorithms aiming to identify stars within the field-of-view (FOV) of a camera to compute the attitude of a satellite. These algorithms are designed to perform without prior knowledge of the attitude of the satellite [1], [10], [11]. The LIS algorithms are usually separated into two families: the *sub-graph isomorphism* algorithms where the stars are seen as vertices of a graph, and the *pattern* ones where each star is associated with a rather unique identifier that is constructed from nearby stars.

One candidate for each family of algorithms is implemented and tested in this study. Because of their contribution to the state-of-the-art in their respective categories, the Multi-Poles Algorithm (MPA) [1] and the Polestar Algorithm (PsA) [2] are selected. Their respective performances toward various sources of noise are tested with simulated images. Then, the differences between those simulated space views and ground-based experimental pictures are surveyed, to highlight the atmospheric effects upon the images. Finally, the two algorithms are adapted to match their original publication's star distribution by modifying the star catalogue and their internal parameters. With those adaptations, the algorithms can be tested directly with ground-based images, while maintaining a success rate of at least 80%.

II. LOST-IN-SPACE ALGORITHMS

A brief overview of the selected algorithms is provided in the next subsections and their internal parameters are introduced. Such parameters will then be modified during the adaptation procedure to try to match the theoretical performance with the experimental images.

A. Multi-Poles Algorithm

The Multi-Poles Algorithm (MPA) is a *sub-graph isomorphism* algorithm published by Schiattarella et al. in 2017 [1]. It is especially resistant to false stars, designed to withstand a high number of Single Event Upsets (SEU) in the image, mainly generated by cosmic radiations in space. Its complete description is available in [1], but some internal parameters

necessary for this study are presented below. The algorithm runs over 3 main phases, and tries to identify the sensor stars with the catalogue by a voting system based on the angular distance between stars. It starts with a recursive loop of acceptance phases where selected stars are paired by angular distance with their neighbors. Then, a verification phase searches for identical pairs of pole stars, from different acceptance phases. A final confirmation phase is done to ensure that every star identified is correct, and to filter any false star and SEU that could have passed through the verification process. The MPA has been implemented with the following parameters:

- *Maximum number of poles:* $R_p = 20$. This number means that after trying R_p different stars through the acceptance-verification loop, the algorithm will stop.
- *Angular distance tolerance:* $\varepsilon_\pi = 1 \text{ arcmin}$. This is the maximum variation in angular distance $\theta_{ij,cat}$ between two catalogued stars s_i, s_j and the corresponding sensor distance $\theta_{ij,sensor}$ such that (s_i, s_j) is accepted as a candidate pair:

$$|\theta_{ij,cat} - \theta_{ij,sensor}| \leq \varepsilon_\pi \quad (1)$$

B. Polestar Algorithm

The Polestar Algorithm (PsA) is a *pattern* algorithm published by Silani and Lovera in 2006 [2]. In opposition to the sub-graph isomorphism algorithms, the information stored in the on-board star catalogue is not only distances between couples of stars but includes also star patterns, hence the name of this category. The pattern generation technique creates a rather unique pattern for each star (called the pole star), enabling the identification of the stars by finding the same pattern in an image. In this algorithm, the pattern is a bar code made by rounding the distances between the pole star and its neighboring stars. The candidate stars are then verified by constructing polygons and verifying that the angular distances of their edges match with the star catalogue. The complete description of the algorithms is found in [2], and the internal parameters necessary for this study are presented below. The PsA has been implemented with the following parameters:

- *Subdivision length:* $err_D = 2 \text{ arcmin} = 0.033^\circ$. This is the length between two consecutive radii for the bar code pattern. This is coherent with the 0.02° of the original publication.
- *Angular distance tolerance:* $\varepsilon_{pairs} = 2 \text{ arcmin}$ and $\varepsilon_{triangle} = 3 \text{ arcmin}$. This is the maximum difference accepted for the distance between catalogued stars and sensor stars.

III. TESTING OF LOST-IN-SPACE ALGORITHMS

In this section, the robustness of the algorithms toward various sources of noise is assessed and quantified with simulated images. This analysis will help to determine which parameters are critical for the adaptation of the algorithms in the experimental tests.

The simulated camera used for the computation of the views is a rectilinear camera with a square FOV of 20° and a

resolution of 1024 by 1024 pixels. Its light sensitivity is such that it is able to detect stars up to a magnitude of 6. The Hipparcos (HIP) catalogue from the European Space Agency will be used as the reference for star positions [12]. A total number of 1800 simulated space images was generated to assess the performance of the algorithms, with the following sources of noise.

A. Sources of noise

The performances of the chosen algorithms are assessed with the simulated space views, generated and fed to the MPA and the PsA algorithms. The results of those tests are compared to the experimental values of noise observed in the ground-based images, to identify the parameters that would require an adaptation. The algorithms are tested toward false stars, position noise and magnitude noise, as described below. Please note that sensor noises, i.e. dark current, shot and read out noises, have been simplified as a random noise in the following items.

1) *False stars:* Adding bright points on the image that are not registered in the catalogue, potentially caused by SEU, or other objects. To simulate this effect, a fraction of false stars with a random magnitude ranging from -1 to 6 as well as a random position on the image, is added.

2) *Position noise:* The centroiding techniques used to precisely locate star positions on the image are limited by the light acquisition of the camera, image distortion and resolution. This effect is simulated by shifting the position of the stars on the image by a given number of pixels, in a random direction.

3) *Magnitude noise:* The detected magnitude of the stars can be modified by the dispersion of the light and by the settings of the camera. It means that some stars that should be detected by the camera are invisible, and some stars that should be too faint are captured nonetheless. To simulate this effect, the magnitude of the stars on the image is modified following a Gaussian distribution with a standard deviation ranging from 0 to 1 depending on the desired level of noise. The stars are then filtered so that only the ones that are visible are captured on the image.

The result of the tests on the various sources of noise are summarized in the next section. The reference performance for both algorithms, without any source of noise, is higher than 99%.

B. Results

1) *Multi-Poles Algorithm:* The MPA is able to withstand noise levels of 75% false stars, 1.5 pixels of positional noise and uncertainties of 0.65 for the magnitude while keeping a success rate above 80%. Given the camera resolution of 1024 pixels and the simulated FOV of 20° , this represents a shift in star position of 1.76 arcmin. This value is coherent with the 1.32 arcmin found in the testing of the multi-poles algorithm done in [13], or 1.125 for the tests in [3]. The performance against magnitude noise is also tested, with a success rate of 93% for a level of 0.4. Again, this is close to the 95% success rate for the same noise level in [3]. On average, the MPA

TABLE I
CAMERA PARAMETERS FOR VARIOUS IMPLEMENTATION OF LIS
ALGORITHMS.

Source	Resolution (Mpx)	FOV (°)	Maximum Magnitude
[1]	1	20	6.5
[2]	0.1	7.5x10	7
[3]	1	12	6.5
[13]	4	15	6

was able to identify 40.3 stars on the reference images, with a standard deviation of 14.4, a minimum of 21 and a maximum of 92.

2) *Polestar Algorithm*: The PsA is able to maintain a success rate of 80% with up to 80% false stars, 1.25 pixels (1.46 arcmin) of positional noise and uncertainties of 0.7 for the magnitude. In the original publication, the position noise is applied following a Gaussian distribution, and the 80% success rate is reached for a standard deviation σ_p of about 0.28 pixels, which corresponds to 1.31 arcmin for $3\sigma_p$. The PsA is also tested in [13], and is reported to withstand a shift in star position of 3 pixels for a success rate of 80%, where a simulated FOV of 14.7° with 2048 by 2048 pixels is used. This is equivalent to 1.29 arcmin of shift in star position, again coherent with the aforementioned values. The performances of the PsA are similar to that of the MPA, regarding every source of noise. On average, the PsA was able to identify 12.8 stars on the reference images, with a standard deviation of 1.5, a minimum 8 of and a maximum of 15. Those smaller values can be explained by the internal parameter of the PsA that limits the number of stars investigated to 20.

IV. ADAPTATION OF THE EXPERIMENTAL SETUP

In order to match the star distribution used in the simulated tests, a survey of the experimental camera settings used in the testing of the aforementioned algorithms is drawn. Although star trackers differ in many ways depending on their respective mission, on the targeted accuracy and on the operating environment, there are some common features shared by many star identification pipelines. Star trackers usually have a small FOV, a low pixel count and a high sensitivity. The implementation of LIS algorithms done in [1]–[3], [13] is surveyed to find the camera parameters used in the simulated tests. The results are presented in TABLE I.

The application of these simulated camera settings to experimental ground-based images often produces a degradation of the algorithms' performance which inhibits any proper testing of the algorithms on ground. Therefore, the effect of the atmosphere on the experimental images needs to be considered. The next sections aim at describing and quantifying those effects so that an efficient adaptation procedure can be proposed to match the star distributions between simulated images and ground-based images.

A. Atmospheric effects

The atmosphere has a filtering and scattering effect on the light received from space. Those effects are known as

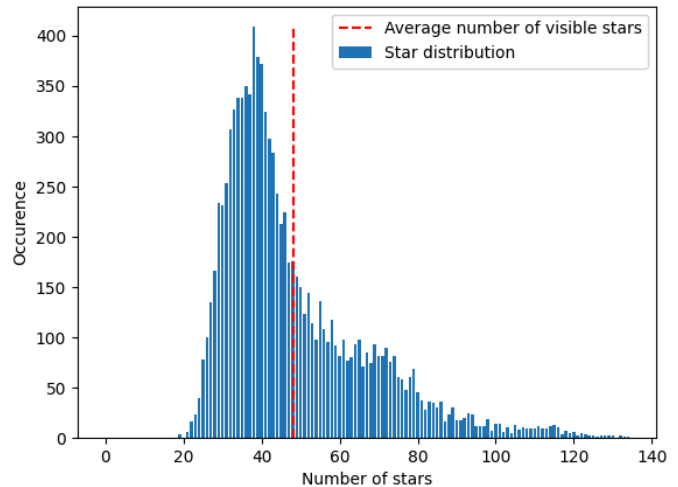


Fig. 1. Number of stars up to magnitude 6 visible in a 20° field-of-view.

atmospheric extinction and atmospheric blurring (or seeing) [14], and are monitored by space observatories [15]–[17].

Atmospheric extinction is the absorption of starlight by the Earth's atmosphere. This absorption is mainly due to Rayleigh scattering by air molecules, to general scattering by fine particles and to molecular absorption by Oxygen and Ozone. This effect is stronger as the airmass above the observer increases. Hence, the level of extinction is lowest around the zenith and highest around the horizon [14].

The atmospheric blurring arises from the various refraction indexes of the atmospheric layers. Those layers have slightly different physical parameters that modify the refraction index, bending the starlight by a different angle depending on the original position of the stars. This effect is further strengthened by the atmospheric motion, that dynamically changes the refraction index over time.

B. Star distribution of the simulated camera

The star distribution visible with the simulated camera with a FOV of 20° and a maximum magnitude of 6 is surveyed, as it needs to be matched by the experimental setup. To have a confident result, 10,000 random orientations are generated and the corresponding distribution for the number of visible stars is reported in Fig. 1. It is possible to see a peak around 40 stars per image with almost 400 occurrences, and an average of 48 visible stars among all the cases.

With zenith atmospheric extinction and suburban light pollution levels due to the atmosphere, the maximum observable magnitude is reduced to 4. The precedent analysis is repeated with the same FOV of 20° and a limiting magnitude of 4. It appears that the average number of visible stars is 5, with a peak at 4, with an occurrence above 1600. In 10% of the orientations, the number of visible stars is less than 1, which makes it impossible to identify the star or compute the attitude.

C. Adaptation of the camera parameters

In order to get closer to the typical in-space star distribution, the FOV, resolution and sensitivity of the experimental camera

need to be adapted. A wider FOV for the camera is necessary, as well as a longer exposure time to capture more stars on the image. A wider FOV implies increasing the resolution in order to keep a sufficiently low arcminute per pixel rate. In the experimental setup, this quantity is around 1.17 arcminute per pixel. The experimental setup used in this study is a SM-G960f rear camera, with a square FOV of 51.35°, and a resolution of 3024 by 3024 pixels. This new resolution means that a pixel corresponds to 1.02 arcminute. The default exposure time is 0.2 seconds, but this value is increased to 10 seconds in order to capture stars up to magnitude 5. With this new setup, the average number of visible stars is 96, with a minimum number of visible stars per image above 50. This distribution involves a lot more stars than the one of the simulated views in Fig 1, which is due to the larger FOV.

Although the modification of the FOV and the exposure time allowed to drastically increase the number of visible stars on the image, the atmospheric blurring is still increasing the inter-star angular error as well as the image distortion. In order to reduce the intrinsic distortion of the image, the camera parameters are estimated using the chessboard method [18] to undistort the images afterward. After this step, the experimental shift for star positions observed on the image is reduced to approximately 5 arcminutes. It means that the inter-star distance can have an error of up to 10 arcminutes, which is higher than the value of ε_π used in the definition of the MPA with the simulated views. It is also higher than the maximum level of shift in star position used in the simulated tests. The change in ε_π has a direct effect on the number of pairs found in the star catalogue, thus increasing ε_π will increase the spurious correlations for a given inter-star distance.

In order to monitor the raw performance of the PsA and the MPA, 35 experimental pictures are taken with this setup. The only modification made in the implementation of the algorithms is the restriction of the catalogue to match the maximum magnitude of 5, as well as the inter-star error set to 10 arcminutes. With this implementation, the success rate of the MPA is 30%, and the success rate of the PsA is 10%. This shows that the algorithms need to be adapted, as solely adding more stars to the image results in a poor success rate.

V. ADAPTATION OF THE ALGORITHMS

The adaptation of the algorithms aims at increasing their experimental performance, by modifying the catalogue, the number of bright stars, and their internal parameters.

The first modification relates to the star catalogue, the idea is to keep only the ξ brightest stars of an image in order to stay close to the simulated distribution. The maximum magnitude of the ξ^{th} brightest star of the image is estimated given the FOV of the camera and the distribution of the HIP catalogue. As the star distribution amongst increasing magnitude is nearly exponential, diminishing the maximum magnitude is greatly reducing the potential mismatches.

The next modification involves the precise estimation of the inter-star angular error given the atmospheric blurring and the residual distortion after the correction. This will help to reduce

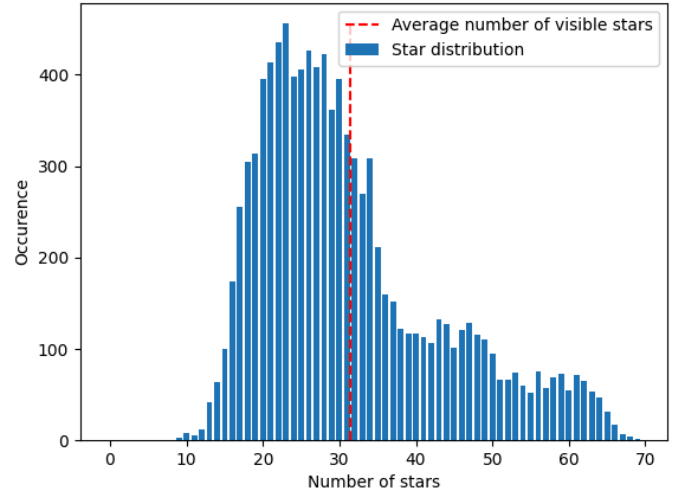


Fig. 2. Number of stars up to magnitude 4 visible in a 51.35° FOV.

the threshold for the error ε_π , thus further reducing the number of spurious matches.

A. Catalogue reduction

The cumulative number of stars per magnitude level is following an exponential law, so a diminution of the maximum magnitude has a very strong impact on the number of stars visible by the camera. Additionally, the star distribution for a FOV of 51.35° and a maximum magnitude of 4 is surveyed and presented in Fig.2. The average number of visible stars is 31, which is sufficient to run the LIS algorithms and derive the attitude. This is close to the simulated star distribution given in Fig.1. Therefore, the maximum magnitude is restricted to 4.

Furthermore, in 90% of the orientations, more than 20 stars are visible. It means that in more than 90% of the cases the $\xi = 20$ brightest stars have a magnitude of 4 or below. This value gives an insight into how many stars have to be fed to the LIS algorithms to work properly with the HIP catalogue. If the star catalogue is restricted to a given magnitude, then all the stars above this magnitude will not be included in the catalogue, thus being considered as false stars. In order to feed only the ξ brightest stars to the LIS algorithm, the bright points detected during the image processing step of the star tracker pipeline need to be weighted by their relative intensity.

At this point, the HIP catalogue has been modified. But the LIS algorithms still need to be adapted, and take into account the previous modifications.

B. Multi-Poles Algorithm adaptation

The following parameters of the MPA are adapted.

- *Maximum number of poles:* $R_p = \xi = 20$. All the stars fed to the algorithm can be tested for the poles.
- *Angular distance tolerance:* $\varepsilon_\pi = 5.5$. This parameter is obtained after some fine-tuning, as explained below.

In order to find a precise value for ε_π , several values are tested, ranging from 1 arcminute to 15 arcminutes. The result

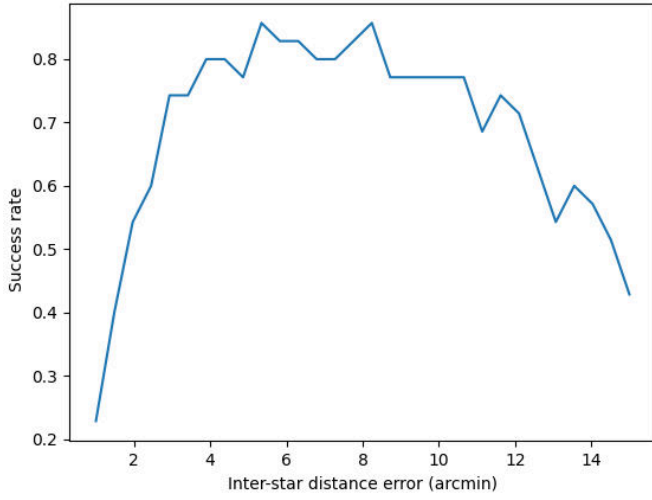


Fig. 3. Success rate for the Multi-Poles algorithm, for various values of inter-star distance error.

of this analysis is available in Fig. 3. When the inter-star distance error is too small, the performance decreases because it is impossible to find a sufficient number of matches within the star catalogue for the image's stars. On the other hand, when ε_π is higher than 10 arcminutes, the performance decreases because the spurious matches within the star catalogue outnumber the correct stars. Good values for ε_π are then ranging between 4 and 8 arcminutes, with a peak success rate of 86% for $\varepsilon_\pi = 5.5$ arcminutes.

C. Polestar Algorithm adaptation

The PsA has more internal parameters than the MPA, and the following modifications have been made, with an important change for the subdivision length err_D .

- *The number of pole stars that are used to generate the bar codes.* This number has the same behavior as R_p in the case of the MPA, so the value of $\xi = 20$ is used, to stay coherent with the restriction of the catalogue and the star distribution.
- *Angular distance tolerance ε_{pairs} .* It has the same meaning as ε_π for the MPA, so the same value of 5.5 arcminutes is used.
- *Subdivision length $err_D = 10$ arcminutes.* This value is more difficult to define, as it has a direct impact on the length of the bar code, and the success rate of the algorithm. The fine-tuning of this parameter is explained hereafter.

The length of the bar code is defined by the number of concentric circles drawn around a pole star. This number is determined by the length of the stripes, which is err_D . The test of various values of err_D is presented in Fig. 4. The performance of the Polestar algorithm stays nearly constant as long as err_D is above 10 arcminutes. This value is interesting because it is approximately twice the value of ε_π . As the star position is not very precise, it can be shifted toward any given direction by a fraction of ε_π , which means a region of $2\varepsilon_\pi$ is

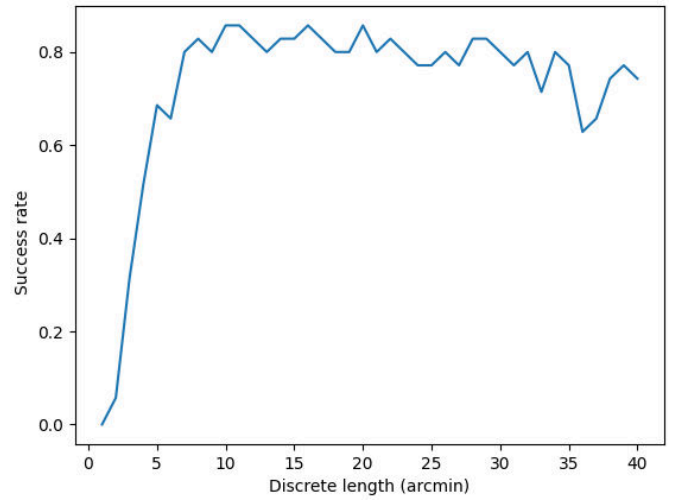


Fig. 4. Success rate for the Polestar algorithm, for various values of the discrete step err_D .

enough to make up for the imprecision, as explained in [2]. Indeed, the best choice seems to be $err_D = 10$ arcminutes, for a success rate of 86%. Ultimately the success rate is bound to drop when the err_D is too high, because the length of the bar code N_{max} will be too small to discriminate between the catalogue stars.

VI. CONCLUSION

This study demonstrated that adaptations are necessary in order to test LIS algorithms with ground-based images, while maintaining a good success rate. Those adaptations involve both the process of capturing and processing of the images, as well as the modification of the intrinsic parameters of the LIS algorithms. Adaptation on the capture and processing of the images involves the increase in exposure time and field-of-view in order to capture more stars on the image, as well as the restriction of the catalogue to match the simulated star distribution. On the other hand, the modifications to the internal parameters of the LIS algorithms are necessary to better match the experimental inter-star distance error.

With those adaptations, it was possible to obtain a success rate of 86% for both the MPA and the PsA algorithms, which is comparable to the performances obtained with simulated images for noise levels of 1 to 1.5 pixels of shift in star position, a magnitude uncertainty of 0.65 to 0.7, and a false star rate between 80% and 90%. Even though the experimental performances are slightly lower than the simulated performances, the results show that this procedure can be used to mitigate some of the atmospheric effects applied to the ground-based images, and proficiently allows for preliminary tests of LIS algorithms.

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REFERENCES

- [1] V. Schiattarella, D. Spiller, and F. Curti, "A novel star identification technique robust to high presence of false objects: The multi-poles algorithm," *Advances in space research*, vol. 59, pp. 2133–2147, 2017.
- [2] E. Silani and M. Lovera, "Star identification algorithms: Novel approach & comparison study," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 42, p. 14, 2006.
- [3] X. Wei, D. Wen, Z. Song, J. Xi, *et al.*, "A star identification algorithm based on radial and dynamic cyclic features of star pattern," *Advances in Space Research*, vol. 63, pp. 2245–2259, 2019. DOI: 10.1016/j.asr.2018.12.027.
- [4] M. Samaan, S. Steffes, and S. Theil, "Star tracker real-time hardware in the loop testing using optical star simulator," Jan. 2011.
- [5] F. Nuno, L. Jones-Wilson, S. Mohan, K. Lo, *et al.*, "Miniaturized star tracker stimulator for closed-loop testing of cubesats," *Journal of guidance, control and dynamics*, vol. 40, 2017.
- [6] K. M. Riesing, H. Yoon, and K. L. Cahoy, "Rapid telescope pointing calibration: a quaternion-based solution using low-cost hardware," *Journal of Astronomical Telescopes, Instruments, and Systems*, vol. 4, no. 3, p. 034002, 2018. DOI: 10.1117/1.JATIS.4.3.034002.
- [7] A. G. Sreejith, J. Mathew, M. Sarpotdar, R. Mohan, *et al.*, "A raspberry pi-based attitude sensor," *Journal of Astronomical Instrumentation*, vol. 03, no. 02, p. 1440006, 2014. DOI: 10.1142/S2251171714400066.
- [8] E. Cordelli, P. Schlatter, P. Lauber, and T. Schildknecht, "Use of a night-tracking camera for characterization and orbit improvement of defunct spacecraft," in *1st NEO and Debris Detection Conference*, Mar. 2019.
- [9] D. Liu, X. Wang, Z. Xu, Y. Li, *et al.*, "Space target extraction and detection for wide-field surveillance," *Astronomy and Computing*, vol. 32, p. 100408, 2020. DOI: <https://doi.org/10.1016/j.ascom.2020.100408>.
- [10] B. B. Spratling and D. Mortari, "A survey on star identification algorithms," *MDPI*, pp. 94–108, 2009. DOI: 10.3390/a2010093.
- [11] D. Rijlaarsdam, H. Yous, J. Byrne, D. Oddenino, *et al.*, "A survey of lost-in-space star identification algorithms since 2009," *MDPI*, p. 18, 2020. DOI: 10.3390/s20092579.
- [12] M. Perryman, "The hipparcos and tycho catalogues, volume 1," ESA, Tech. Rep., 1997.
- [13] Q. Fan and X. Zhong, "A triangle voting algorithm based on double feature constraints for star sensors," *Advances in Space Research*, vol. 61, pp. 1132–1142, 2018.
- [14] B. E. Schaefer, "Atmospheric extinction effects on stellar alignments," *Archaeoastronomy*, vol. 10, p. 11, 1986.
- [15] F. Patat, S. Moehler, K. O'Brien, E. Pompei, *et al.*, "Optical atmospheric extinction over cerro paranal," *Astronomy and Astrophysics*, vol. 257, p. 14, 2011.
- [16] F. Rufener, "The evolution of atmospheric extinction at la silla," *Astronomy and Astrophysics*, vol. 165, p. 12, 1986.
- [17] G. Burki, F. Rufener, M. Burnet, C. Richard, *et al.*, "The atmospheric extinction at the e.s.o la silla observatory," *Astronomy and Astrophysics supplement series*, vol. 112, pp. 383–394, 1995.
- [18] R. Hartley and A. Zisserman, *Multiple View Geometry in Computer Vision, Second Edition*. Cambridge University Press, 2003.



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Jannin, Louis; Felicetti, Leonard

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