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in: 2nd International Conference on Applied Intelligence and Informatics (AII2022), 2023, p. 1-12 [2nd International Conference on Applied Intelligence and Informatics (AII2022), Reggio Calabria, Italy, 1-3 Sept. 2022]

Deep Learning for Navigation of Small Satellites about Asteroids: an Introduction to the DeepNav Project

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Abstract. CubeSats represent the new frontier of space exploration, as they provide cost savings in terms of production and launch opportunities by being able to be launched as opportunity payloads. In addition, interest in minor bodies is gradually increasing because of the richness and exploitability of the materials present throughout their surface, the scientific return they could yield, and their dangerousness. Moreover, they are characterized by a highly harsh environment. These are the reasons why greater autonomous capabilities are desirable for future space missions. Optical navigation is one of the most promising technique for retrieving spacecraft state, enabling navigation autonomy. Unfortunately, most of these methods cannot be implemented on-board because of their computational burden. ~~are heavy and slow, which prevents their on-board implementation~~. This paper presents the "Deep Learning for Navigation of Small Satellites about Asteroids" project, in short "DeepNav", whose aim is to change the current navigation paradigm by exploiting artificial intelligence algorithms for on-board optical navigation. As a result, DeepNav will evaluate the performance of fast and light artificial intelligence-based orbit determination for the proximity operations phase around asteroids.

1 Introduction

Over the past decades, governments, space agencies, and private companies have recognized micro- and nano-satellites as appealing platforms for

pursuing a wide range of objectives in space, including science, technology demonstration, and Earth observation. With significant cost reductions compared to traditional large satellite missions, these systems offer the opportunity to increase the number of spacecraft launches and enable faster manufacturing development. Among these classes of platforms, the CubeSat standard has become extremely popular. Nano-satellite constellations in low-Earth orbit (LEO) are becoming a reality, while the scientific and industrial community is exploring applications of nano-satellites for interplanetary missions [11]. These, represents new challenges compared to LEO missions, such as surviving in a harsher space environment, communicating with Earth from a greater distance, achieving accurate pointing without exploiting the magnetic fields of celestial bodies, and performing accurate orbital maneuvers. In addition, a paradigm shift is needed when operations are considered: while miniaturization of technology has already enabled a significant reduction in the cost of space segment, the ground segment cost do not scale with satellite size. Ground stations used for deep space missions present high operational costs that are not sustainable with the low costs of nano-satellite missions. These costs are due to the allocation of a flight-dynamic team, big antennas for deep space communications must be scheduled to be operated, and the competition with other missions for access to communications slots [8].
In addition, interest in asteroid exploration is pushing forward for several reasons: they contain an abundance of valuable resources including platinum, gold, iron, nickel, and rare metals, evenly distributed throughout small bodies' mass [1]. Moreover, they could be used as refueling stations to overcome the technological limits of deep space exploration. Their study could allow to understand the solar system evolution and the accretion process of planets. Moreover, several potential hazardous asteroids (PHAs) have been estimated [5].
Several missions have been performed to study, among others, composition, shape and gravity of these bodies, as measurements from Earth give just approximate information. Therefore, the need to autonomously navigate around these bodies arises. The capability of a navigation system to provide an accurate estimate of spacecraft state strongly depends on the mission scenario, environment, and platform constraints. Optical Navigation (OpNav) represents the most promising autonomous method. It consists of a set of techniques used to obtain an estimate of the spacecraft state from images. The observer state estimation is a process made of different steps. As far as optical navigation is concerned, the first step consists in the image acquisition. The images are processed to extract relevant optical observables, and finally they are further elaborated by an estimation scheme and a navigation filter to retrieve the spacecraft state. These algorithms could be slow and heavy for on-board implementation and so far have been mainly used on regular shaped asteroids and moons. Artificial Intelligence (AI) algorithms can be used to bypass the various steps of traditional methods by directly obtaining the state from the image. In addition, they can be leveraged to increase the achievable accuracy by enhancing generalization capabilities in the proximity of irregularly shaped objects. Furthermore, AI methods enable light and fast computations when facing complex scenarios that would be difficult to

process with traditional methods.
The project aim is to evaluate AI-based, Orbit Determination (OD) performance for the proximity operations phase around asteroids. The operative scenario considered is the resolved one, in which the target is a finite-sized object within the camera field of view (FOV). This is the richest and most complex navigation scenario, where surface morphological features, such as craters and boulders, are resolved. For such a scenario, AI and machine learning can enable fast and accurate extraction of relevant information from images that have a high level of detail and a great amount of information.

In this context, the DeepNav (Deep Learning for Navigation of Small Satellites about Asteroids) project was recently selected by the Italian Space Agency, as part of a competitive call focused on the development of new navigation technologies.
The consortium is composed by entities and institutions from Italy. Consortium prime is AIKO[5], responsible of artificial intelligence research and development for asteroid navigation algorithms, support in integration, testbed execution, and analysis of results. Politecnico di Milano, and in particular the DART[6] team, responsible of research and development of navigation algorithms, testbed development, test execution and analysis of the results. CIRI Aerospace, Università di Bologna, and in particular the Radio Science and Planetary Exploration Laboratory[7], is in charge of the definition of the use cases and requirements, study of simulation environment and navigation filters, implementation of breadboard and related software, support to execution of tests and analysis of results.

The rest of the paper is organized as follows. First, the framework where the DeepNav project is focused is highlighted, with a brief introduction to optical navigation and navigation scales. After such discussion, the goals of the project and the methodology that will be applied to achieve them are described. Expected outcomes are reported, and finally, some conclusions are discussed.

2 Framework

2.1 Optical Navigation

Optical navigation consists of a set of techniques used to obtain an estimate of the spacecraft state from images. As far as optical navigation is concerned, diffeent steps are involved, starting with the images acquisition. The images are processed to extract relevant optical observables, and finally they are further elaborated by an estimation scheme and a navigation filter to estimate position and velocity of the observer.

[5] https://www.aikospace.com/, last access: 31/05/2022
[6] https://dart.polimi.it/, last access: 31/05/2022
[7] https://site.unibo.it/radioscience-and-planetary-exploration-lab/en, last access 31/05/2022

Image Processing The state estimation accuracy is strongly affected by the image processing method used for the optical observable extraction. In deep space, the only available optical observables are the line-of-sight directions of visible objects. Such directions are usually obtained thanks to centroiding algorithms. Regarding the far proximity range, the apparent dimension and the shape of the celestial body are estimated exploiting edge finding and centroiding algorithms. On the contrary, for close proximity operations, there is a need for algorithms able to identify features line-of-sights or to trace their geometry.

Estimation Schemes The estimation schemes take as input the optical observables extracted from image processing. The final objective consists in the preliminary estimation of position and velocity through navigation methods. The most common estimation schemes employ line-of-sight information to use triangulation or least squares estimation techniques. Other traditional navigation techniques elaborate the shape and size of the objects by exploiting perspective geometry rules.

Navigation Filters Estimation schemes do not return sufficiently accurate results about the observer's state. Thus, the last step to obtain an accurate state vector is represented by filtering methods. In doing so, knowledge of the dynamics combined with environmental measurements is exploited to obtain an accurate estimate of the observer's state.

The increasing interest in optical navigation is due to the enhanced request for spacecraft autonomy. The DeepNav project will focus on the close range regime, and will exploit Artificial Intelligence to provide robust solutions regarding feature detection, matching, and to perform the 6D Pose Estimation task. Below, for the seek of completeness, will be a brief survey of all the traditional algorithms, some of them used in previously flown missions to navigate minor bodies by landmarks, and therefore in the close proximity regime.

Navigation Scales Satellite navigation is based on the processing of some measurements, which in the case of optical navigation are acquired from the surrounding environment. This involves the definition of different navigation scales, deeply discussed in [4]: deep space, far range, and close range. Navigation scales can be classified based on the feature pixel ratio (FPR), defined as the ratio between the feature and the pixel angular dimensions (γ and θ, respectively) [4]:

$$FPR = \frac{\gamma}{\theta} \tag{1}$$

Deep Space The distance between the observer and the solar system object is large. In this condition the object is identified as a bright spot in the image plane, as it occupies few pixels. In this condition the $FPR \approx 0$, thus a pixel of the detector contains a large portion of the object, as visible in Fig. 1.

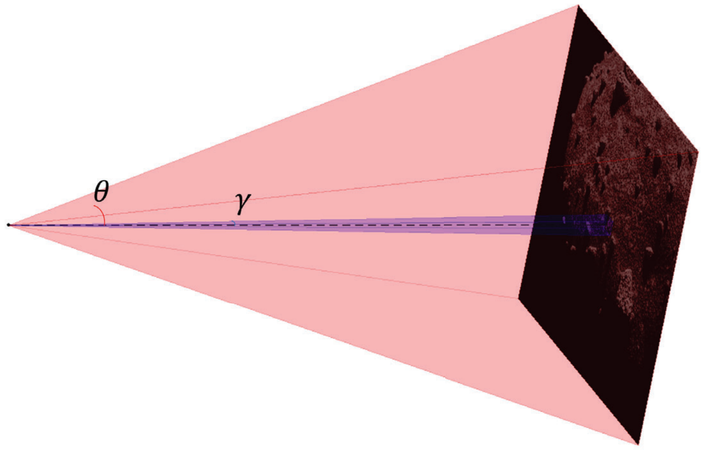


Fig. 1: Visibility of a detector pixel in deep space condition. The angular size of the pixel is depicted in red, while the feature angular size in blue.

Far Range In the far range scenario, the object occupies a large portion of the camera field of view and the shape is resolved. In Fig. 2, it is possible to see how multiple features are grouped in a pixel resulting in a $FPR \leq 1$.

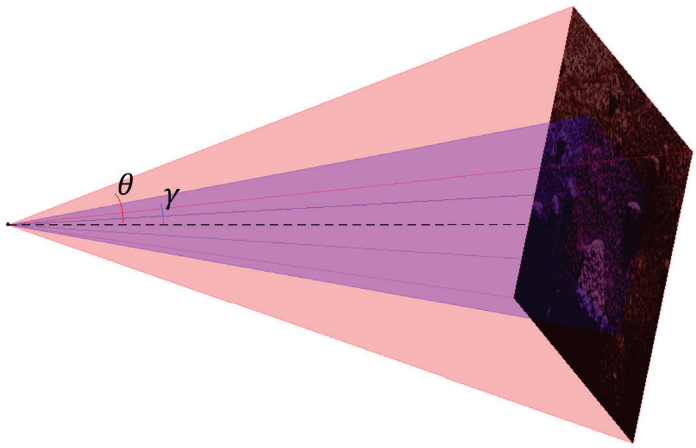


Fig. 2: Visibility of a detector pixel in far range condition. The angular size of the pixel is depicted in red, while the feature angular size in blue.

Close Range The camera is close to the body so that details and surface morphological features are visible and fully resolved. This is the richest optical navigation scale, since many details of the target object such as craters, boulders, and mountains come to light. This scenario will be addressed by the DeepNav project. When a single feature is mapped by several pixels, as shown in Fig. 3, the FPR is greater than one, and the navigation scale is of close range. In this condition the features on the surface of the minor body are fully resolved enabling feature tracking algorithms. Tab. 1 shows the FPR values in relation to the navigation scale.

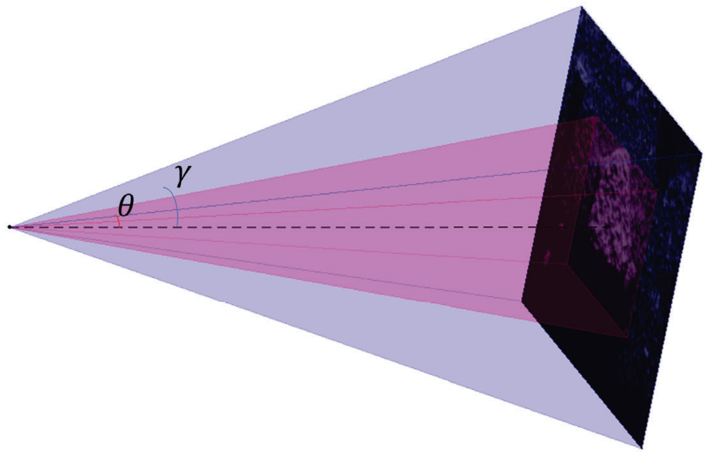


Fig. 3: Visibility of a detector pixel in close range condition. The angular size of the pixel is depicted in red, while the feature angular size in blue.

Table 1: Definition of navigation scales.

	Deep Space	Far Range	Close Range
FPR	≈ 0	≤ 1	> 1

Algorithms for Absolute and Relative Navigation Data extracted from cameras return line-of-sight information of interesting points. In this way, the scale ambiguity problem cannot be solved if no maneuvers are performed during the observation of the body.
As described in [6], two types of navigation can be defined: relative and

absolute. Relative navigation returns a measure of the camera displacement with respect to an unknown reference frame. Contrary, absolute navigation allows to get the camera position with respect to a known reference system, resulting in a complete determination of its position.
An example of relative navigation algorithm is feature tracking. Since the feature-camera distance is not determined, it is not possible to derive the absolute translation value from the features motion. The motion is performed with respect to an unknown reference as the features are not associated with a known morphological map.
Absolute navigation is based on landmarks, where the observed features are linked to a well known landmark map. The landmarks are expressed in a known reference frame, resulting in the computation of the camera position in this frame. In this way, the motion can be completely reconstructed.

3 Project Development

3.1 Project Objectives

Within this context, the goal of the project is to:

> Design and validate up to TRL4 an autonomous orbital determination subsystem for small satellite platforms based on on-board acquired optical imagery for close proximity asteroid navigation scenarios using artificial intelligence techniques.

Three sub-objectives can be defined to achieve this purpose:
- Design and demonstration of an autonomous orbital determination subsystem for small platforms based on on-board acquired optical images.
- Research and implementation of deep learning algorithms for image processing and extraction of information to be used by navigation algorithms.
- Development of a testbed with novel technical characteristics, compatible with small satellite missions, and with relevant computational power.

3.2 Methodology

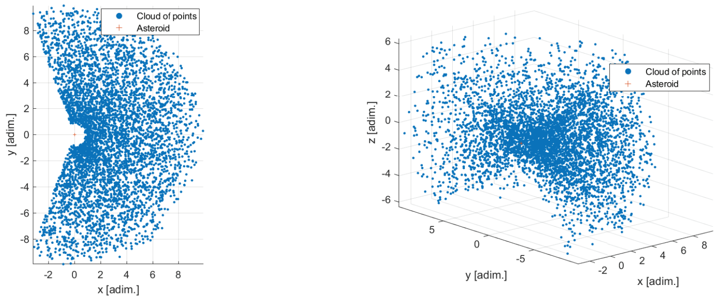
The DeepNav project is scheduled to last 18 months and can be divided into four distinct phases, ranging from literature study to analysis of results via software and hardware implementation of innovative navigation algorithms. The first phase of the project consists of a literature review of traditional and artificial intelligence algorithms in navigation-related scenarios inserire esempi di algoritmi di AI. A trade-off in complexity, performance, robustness, and computational burden will be carried out to select the most promising ones. In addition, algorithms for procedural generation of synthetic landmarks on the surface of minor bodies (such as craters and boulders) will be investigated. Finally, the most promising use case scenario with associated navigation requirements will be selected.

The second part of the project consists of the software implementation of the selected algorithms via Python scripting. Regarding artificial intelligence algorithms, the most suitable training strategy (supervised, semi-supervised and unsupervised) will be selected based on the chosen use case. Traditional relative and absolute navigation algorithms will be implemented and their on-board implementation will be investigated. A dataset of high fidelity synthetic images of minor bodies, as shown in Fig. 4, will be made with an in house developed tool [2] for training, validation, and testing purposes. The dataset will be generated by creating a point cloud around the illuminated side of the asteroid in order to capture it at all possible phase angles and poses obtainable during a mission. An example of such a point cloud is shown in Fig. 5. In addition, for testing purposes, feasible trajectories around the body will be simulated. Two different datasets will be built: the first for software-in-the-loop purposes, the latter to be compatible with the screen resolution of the optical facility. The process for the generation of the datasets is shown in Fig. 6. Navigation Kalman filters for non-linear scenarios will be implemented and the design of the software and hardware navigation subsystem will be carried out. The performance of the entire navigation algorithm will be evaluated by testing it on synthetic images for the defined use case.

The third phase consists in the optimization of the algorithms for embedded hardware implementation and evaluating their performance ~~, checked with appropriate metrics~~ in terms of trajectory reconstruction error, runtime performance, and covariance realism. Image processing algorithms will be integrated with filtering ones [9] for the accurate orbit determination and software-in-the-loop tests will be performed for validation. In the meantime, the development and integration of the optical testbed based on the requirements of the project will be carried out.

Finally, in the last phase, the achievement of TRL4 will be demonstrated through a hardware-in-the-loop (HIL) test campaign involving the setup of a dedicated testbed, TINYV3rse [7], designed at the DART Lab and shown in Fig. 7, simulating a feasible mission scenario. The autonomous navigation technologies developed will be potentially applicable to specific ongoing mission studies employing CubeSats. Among the most recent are the M-ARGO [10] and LUMIO [3] missions. The first is a mission to characterize unknown asteroids in the Solar System, while the second is a mission to study meteoroids in the cis-lunar environment by characterizing the flashes that are produced as a result of impacts on the Moon. Both missions may benefit from the use of autonomous navigation techniques for their cruise or proximity phases.

Fig. 4: Sample images of asteroids Itokawa and Bennu at different poses, distances, and lighting conditions.



(a) (b)

Fig. 5: Example of cloud of points used for training/validation. The Sun is illuminating from the $+x$ direction.

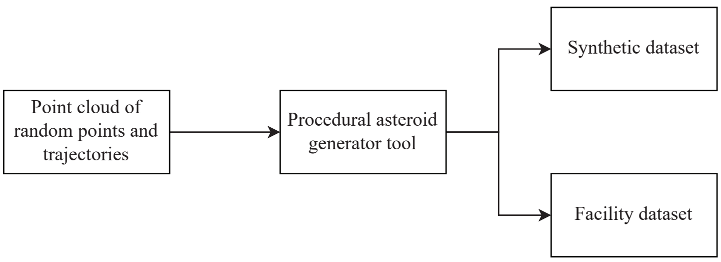


Fig. 6: Logical flow for the construction of the datasets that will be exploited during the project.

4 Expected Outcomes

DeepNav will demonstrate autonomous navigation technologies for CubeSats, such as:

- Demonstrate the benefits and evaluate the performance of AI-based autonomous techniques for deep space missions;
- Concrete validation of the applicability of miniaturized sensors and technologies for low-cost and high-throughput scientific and exploration space missions.

DeepNav will enable significant cost reductions by paving the way for new types of deep space missions, such as:

- Autonomous exploration and characterization of a variety of asteroids and small objects.
- Frequent exploration of well-known Solar System bodies for scientific purposes.
- Low-cost, high-throughput scientific missions to unknown bodies in the Solar System.

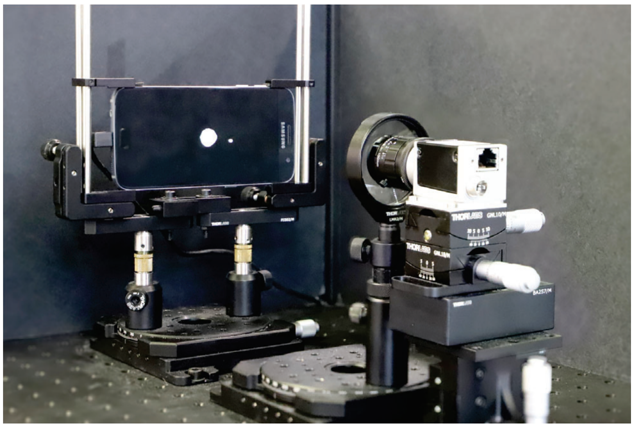


Fig. 7: TINYV3rse testbed for the DeepNav project.

5 Conclusions

Deep Learning for Navigation of Small Satellites on Asteroids (DeepNav) is an 18-month project funded by the Italian Space Agency (ASI). The consortium is composed of Italian companies and institutions: AIKO, Politecnico di Milano and Università di Bologna. The project aims to improve the exploration capabilities of small bodies by enabling the autonomy of shoe-boxed sized spacecraft, named CubeSats, exploiting images taken on-board and processed with artificial intelligence algorithms. The operative range of the project is the close range one, where each feature is clearly distinguishable in the camera plane. To achieve the project goal, several steps are involved. Literature review is the first phase, moving through implementation of the algorithms at both software and hardware levels. Finally, simulations will be conducted to validate up to TRL4 an autonomous orbital determination system. This document reflects the project proposal, which is currently at the end of the first phase.

6 Acknowledgment

The DeepNav (Deep Learning for Navigation of Small Satellites about Asteroids) project has been financed under ASI Contract N. 2021-16-E.0. M.P and F.T would also like to acknowledge the funding received from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 813644.

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