PIONEERING THE SMALL BODIES FRONTIERS: THE KEY ENABLING TECHNOLOGIES FOR AUTONOMOUS PRECISE MOBILITY

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ABSTRACT

Current exploration missions to the close vicinity of small celestial bodies require plenty of human monitoring and processing to ensure a safe fly during the mission operation. This makes these types of missions complex and rare. By introducing more on-board autonomy into the spacecraft system, small celestial bodies can be explored more efficiently and in a larger area, which increases the overall scientific return of these missions.
This paper focuses on the particular challenges of autonomous precise mobility on Small Solar System Bodies. It presents the challenges and solutions from the research projects Astrone, Astrone KI and NEO-MAPP for autonomoy enabling technology in the field of environment perception (e.g. vision-based navigation) and decision-making. This is made possible by relying on cameras and (flash)-LiDARs. Additionally, tailored AI-based solutions are identified, which can aid the processing of these data. All these novel autonomous functionalities have to be tested with adequate verificaiton and validation facilities. The current and future facilities are discussed.
Taken together, the technologies present a novel autonomous precise mobility on Small Solar System Bodies for both landing and exploration of the surface in close proximity.

1 INTRODUCTION

In recent years, the exploration of small bodies in our solar system, such as asteroids and comets, has gained significant attention due to their scientific value and potential for resource utilization. These celestial bodies offer unique insights into the origins of our solar system and hold valuable resources that could be vital for future space missions. However, conducting missions to these small bodies poses numerous challenges, particularly in achieving autonomous precise mobility.
The frontier in the field of Small Solar System Bodies (SSSBs) exploration lies in achieving autonomy in mission operations. Autonomy refers to the ability of a spacecraft to perform tasks and make decisions independently, without continuous human intervention. In past and current missions, autonomy has been a key focus in enabling spacecraft to navigate, land, and conduct scientific investigations on SSSBs.
This has been achieved by optical relative navigation and radiometric absolute navigation [1]–[4]. Radiometric tracking enables precise absolute tracking the spacecraft's trajectory with repect to the Earth. Landmark-based navigation has utilized identifiable features on the SSSB's surface to aid in spacecraft localization and orientation. Although these technologies led to successful missions, they

rely on continous human monitoring and processing. The landmark-based navigation requires extensive modelling effort on the ground, radiometric measurements are not available at all times, and the landing site is carefully chosen by extensive mapping of the surface. In contrast, a fully autonomous spacecraft would land on the surface and afterwards explore the whole surface independently. By enlarging the exploration range in this way, the overall scientific return of the mission would significantly increase.
To address the limitation of human-in-the-loop, more recent mission progressively included technologies that pushed the autonomy frontier even further. Hayabusa-2 [5], launched in 2014, showcased upgraded navigation instruments and extensive characterization techniques, including radiometric tracking and autonomous descent. OSIRIS-REx [6], launched in 2016, employed, in addition to radiometric tracking, vision-based navigation for close range operations, along with advanced exposure techniques and landmark tracking. Finally, DART [7], launched in 2021, achieved kinetic impact deflection with the help of a fully autonomous navigation systems and avionics.
The assessment of previous missions reveals the utilization of various key enabling technologies for autonomy. Autonomous environment perception (e.g. vision-based navigation) has played a crucial role, allowing spacecraft to determine their position and orientation relative to the target body using visual information. Additionally, decision-making autonomous systems incorporating machine learning and image processing (IP) have been employed for hazard detection, slope estimation, and safe landing site selection.
Advancing the boundaries of autonomy in upcoming missions is crucial as we are reaching the limit of human intervention or ground in the loop for SSSB missions. The need for autonomy becomes paramount to ensure higher performance, particularly when operating at large distances where communication delays pose significant challenges. As missions become more complex, either due to an increase in the number of probes or the exploration of multiple targets, the importance of autonomy is further underscored. Scenarios where multiple spacecraft can independently land and explore asteroid fields with minimal human intervention are evisioned.
To meet these demands, further development of the mentioned technologies is imperative. This includes the advancement of more sophisticated machine learning algorithms that can enable spacecraft to learn and adapt in real-time, improving their decision-making capabilities. Improved sensor capabilities are also vital, allowing spacecraft to gather accurate and reliable data to inform their autonomous operations. This encompasses advancements in optical, infrared, and light detection and ranging (LiDAR) sensors, as well as the integration of new sensing technologies.
Additionally, robust decision-making and adaptive autonomy are crucial for navigating the challenges posed by SSSB missions. These aspects involve developing algorithms and strategies that can handle unexpected events, adapt to changing environments, and make intelligent decisions in complex and uncertain situations. By incorporating robustness and adaptability into the autonomy framework, spacecraft can better handle mission complexities and ensure the success of their operations.
Given this vision, the consortium, comprising Astrone [8], Astrone KI, and NEO-MAPP [9], has undertaken research projects aimed at achieving full autonomy. These projects have resulted in the development of diverse Guidance, Navigation, and Control (GNC) technologies. The NEO-MAPP project primarily focuses on the landing phase, while the Astrone and Astrone KI projects concentrate on advancing surface mobility capabilities.
This paper presents the particular challenges of autonomous precise mobility on SSSBs and breaks them down to GNC functionalities in Section 2. The GNC functions related to autonomous navigation are detailed in Section 3 followed by decision-making functionalities in Section 4. The developed verification and validation testbed facilities to test the GNC functions are outlined in Section 5. Lastly, conclusions are drawn in Section 6.

2 TECHNOLOGIES FOR AUTONOMOUS PRECISE MOBILITY

Two broader autonomy categories have been identified: 1) environment perception, and 2) decision-making. The first category *environment perception* consists of measuring the surrounding to generate a map and localize the spacecraft within this map. The main challenge compared to Earth applications is the GPS-denied enviroment. When the navigation filter does not have any absolute position knowledge, the filter estimates are known to drift due to the accumulation of relative position errors over time. At the same time, the surface geometry is only known up to a certain resolution, so that updates to an onboard map have to be made. Additionally, the computational performance of the oboard computers are much more limited, so that lightweight algorithms have to be employed.
The solution to these challenges is to use optical and ranging sensors in the form of cameras and LiDARs. The developed algorithm for the LiDAR has the advantage of delivering directly three-dimensional measurements, which can be easily integrated into an existing map. Furthermore, it can be used in any illumination condition, so that a spacecraft can also operate on the dark side of the target body. Thus, this algorithm has been developed for the exploration close to the surface. In contrast, the camera-based solution only has two-dimensional data, so that additional information in form of a shape model or from an altimeter is necessary. This disadvantage is offset by its light and compact design. Additionally, it does not have a maximum range unlike the LiDAR. This makes the camera-based algorithm better suited for the landing scenario, where the spacecraft can start several kilometers away from the surface. Taken together, the camera- and LiDAR-based solutions enable autonomous navigation to operate around the SSSB without relying on ground-based tracking or communication.
The second category *decision-making* is the ability to steer the spacecraft away from a nominal trajectory. In both the landing and surface exploration scenario, the trajectory is carefully designed on ground to meet certain landing requirements. However, hazardous objects might not be identified prior to the start, when the objects are smaller than the available surface resolution. Autonomous hazard detection during the flight overcomes this issue, because the surface is observed at a closer range. If a hazard is in the path of the nominal trajectory, a new landing site has to be found and the trajctory has to be adjusted onboard.

Table 1: Breakdown of autonomy to various GNC technologies.

Autonomy Category	**Challenges**	**GNC Technologies**	**Section**
Environment perception	• Localization in GPS-denied environment • Limited computational performance • Limited geometrical map	LiDAR-based navigation Camera-based navigation	[3.1] [3.2]
Decision-making	• Multiple landing requirements • Reliability and accuracy • Adaptability	LiDAR-based hazard detection AI-based LiDAR-free hazard detection AI-based map generation from camera and LiDAR Motion Planning to Explore Unknown Terrain	[4.1] [4.2] [4.3] [4.4]

The challenges for the decision-making is to fulfill multiple landing requirements, e.g. surface slope and roughness, at the same time. The nominal and new landing sites have to be assessed for these requirements with precise accuracy and high reliability. A new trajectory has to be feasible by considering the system constraints, while being able to adapt to the changing perceived environment.
The solutions to these challenges have been splitted analogous to the navigation filters into camera-based and LiDAR-based algorithms. LiDARs directly measure the distance from the spacecraft to the surface making them ideal to detect hazards by processing and assessing the raw data. When no LiDAR is available, camera images can be segmented to detect hazards. An AI-based algorithms is proposed for this task because they have been proven to excel in segmentation. One drawback of the LiDAR solution is that the resolution of this unit is typically much smaller than the resolution of cameras. The fusion of both units into one map is accomplished through an AI-based algorithm. Lastly, a terrain-following algorithm is presented that is capable of exploring unknown regions on the surface by processing the LiDAR's geometrical information.

3 ENVIRONMENT PERCEPTION

The main GNC functionalities for the environment perception are the state estimate in the GPS-denied environment and the generation of a map. Several solutions based on LiDAR and camera data have been developed.

3.1 LiDAR-based Navigation

To enable autonomous operation of a flying vehicle in close proximity to the asteroid surface, 3D navigation with respect to the terrain is mandatory. This requires reliable and accurate 3D terrain perception that is robust to rapid changes of observation geometry, perspective distortion and obscuration. To provide the required navigation solution, a Flash LiDAR-aided inertial navigation system (Figure 1) has been developed within the frame of the Astrone project [10].
Independent Inertial Navigation System (INS) propagates the nominal spacecraft states i.e. the position, velocity and attitude quaternion, given the inertial measurement unit (IMU) measurements (the accelerometer specific force vector and the gyro angular velocity vector). The spacecraft states are defined with respect to a "local-level" coordinate system that is fixed to the SSSB surface (the origin of local frame coincides with the origin of the body frame at take-off).
Flash LiDAR pre-processing uses the Iterative Closest Point (ICP) algorithm to register two point clouds from the Flash LiDAR. The result of the registration is a relative rigid transformation (transla-

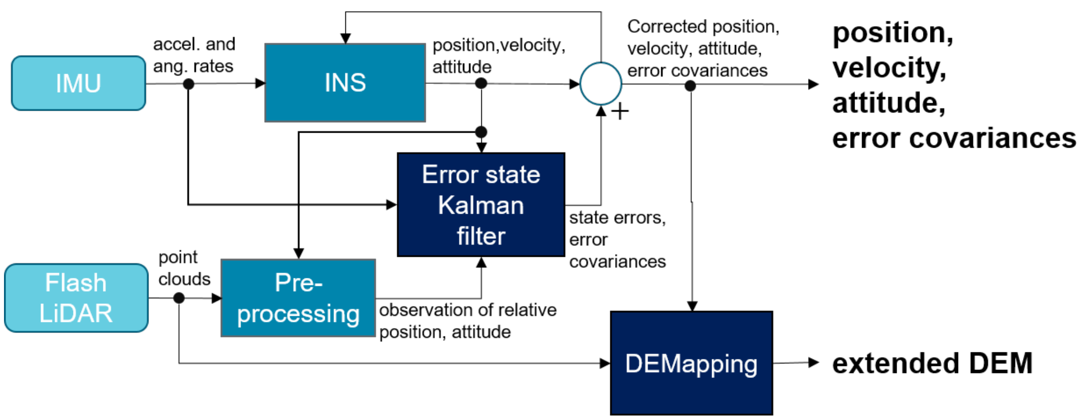

Figure 1: Flash LiDAR-aided inertial navigation system from [8].

tion and rotation) of the spacecraft, which is an external observation of the relative system states and is used to update the error states in the error state kalman filter (ESKF).
The Flash LiDAR aided-INS using ESKF is particularly suitable for the asteroid mission as it allows ESKF to be updated at a lower rate, significantly reducing the computational load and matching the slow dynamics of the spacecraft. In case of ESKF failure, the navigation system can still propagate the system states using INS only. This increases the operational reliability of the navigation system.
The navigation system was implemented in MATLAB / Simulink and successfully tested in a simulated asteroid environment: the required navigation accuracy was achieved for the typical mission scenarios. However, for some specific test conditions, limitations of the pure LiDAR / ICP based solution were observed, in particular a degradation of the point cloud registration accuracy/reliability for the particularly flat terrain with sparse and small 3D surface elements. To improve the reliability and accuracy of navigation data determination, robust 3D features extraction by AI-based joint processing of LiDAR and camera data is currently being investigated within the frame of Astrone KI project.

3.2 Camera-based Navigation

Conventional methods of navigating asteroids typically follow a similar pattern, involving distant radiometric tracking followed by a characterization stage. The information obtained during characterization is then utilized to independently guide the spacecraft towards the asteroid, eliminating the need for communication with Earth [6].
Enhancing spacecraft autonomy, particularly reducing reliance on Earth-based radiometric tracking, presents a significant hurdle in asteroid navigation. Radiometric tracking is costly and restricts the spacecraft's safe operating range. Additionally, the Deep Space Network, which provides radiometric tracking measurements, has limitations in supporting multiple spacecraft. Moreover, smaller and more affordable spacecraft may not have access to radiometric tracking. Consequently, these spacecraft must navigate with a limited array of sensors. Previous missions have demonstrated the feasibility of autonomous navigation after an initial characterization phase that heavily relied on radiometric tracking. Overcoming the challenge of bypassing this expensive and time-consuming early characterization phase is crucial.

3.2.1 Far Range Navigation

Researches within NEO-MAPP project [9] have been focusing on developing navigation systems that utilize optical measurements from cameras and laser range finders (LRFs) to estimate the spacecraft's position relative to the asteroid. Additionally, star trackers and rate gyros are employed to determine the spacecraft's attitude.
Camera measurements provide valuable information such as the line of sight, centroid and apparent diameter, and landmark tracking. However, these measurements are affected by range ambiguity, especially as the altitude increases and landmarks appear smaller in the images. To address this, triangulation techniques can be used when multiple bodies are observed by the cameras. Alternatively, a formation of spacecraft can resolve the range ambiguity issue if inter-spacecraft measurements are available. Another common approach is to combine navigation cameras with LiDAR or LRFs to overcome range ambiguity.
Recent studies have shown promising results in achieving autonomous navigation in a binary asteroid environment by solely observing the primary asteroid or using LRFs with an ellipsoid shape model. The NEO-MAPP research novelties in this field include the utilization of a sensor suite that is not commonly used in literature, as well as considering a mission scenario where updated ephemeris information is relayed from the mothership to the lander. The challenge in this scenario arises from the lack of separation between the primary and secondary bodies, making angles-only navigation

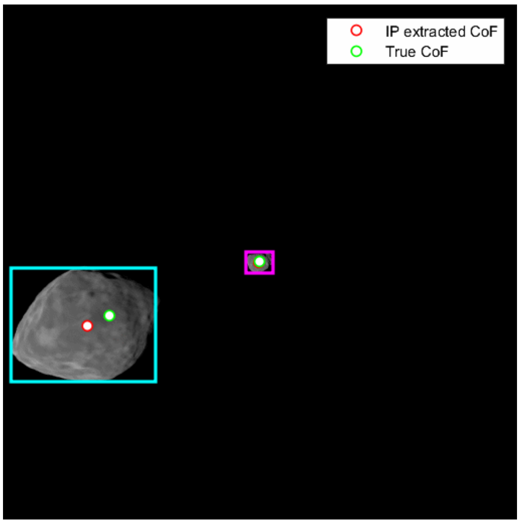

Figure 2: Far range navigation with true (green) and extracted (red) centre of figure (CoF).

impossible. However, the research aims to extract information about both bodies from the images captured during different phases of the flight. Additionally, the use of a LRF without a high-fidelity surface model is explored, which has been previously studied in combination with landmark tracking for absolute navigation.
NEO-MAPP proposes an autonomous navigation solution for small spacecraft in a binary asteroid environment. It extends on previous work that investigated the effectiveness of LRFs and cameras for navigation in (binary) asteroid environments. An extended Kalman filter with nine parameters in the state vector is shown to successfully estimate the spacecraft state in an inertial reference frame. Prior knowledge of the asteroid ephemeris and ellipsoidal shape model is required to connect the relative measurements to the inertial frame. The IP that extracts measurements from the camera images is identified as a pivotal component with a large influence on the performance of the filter.
Its performance is impacted by high sun phase angles and irregular asteroid shapes. It is shown that for an irregular asteroid shape and for high sun phase angles, the quality of the measurements is still sufficient to perform the state estimation. Furthermore, the navigation solution is shown to be very robust to uncertainty in its initial state estimate.
The state is also observable without the LRF, given that there is good visibility of both asteroids. Finally, the navigation solution was tested with distorted and noisy camera images, to which the filter responded in a robust manner without any failure. The navigation solution developed in this work is therefore a robust option for medium to close range navigation in a binary asteroid environment.

3.2.2 Close Range Navigation

Close range autonomous relative navigation is a crucial aspect of the terminal phase of landing in Small Solar System Body (SSSB) missions. In this phase, where the secondary body occupies the entire field of view, a feature-based approach is employed due to the inability to estimate the centroid. Features are extracted and tracked from observed images, and in conjunction with LRF measurements, they are utilized to estimate the lander's state. This approach focuses on observing the relative state with respect to the surface and is specifically designed for short distances from the surface. The main contribution of the work in NEO-MAPP lies in the development of an innovative navigation filter that effectively combines features and LRF measurements, ensuring high accuracy and reduced drift in the solution.

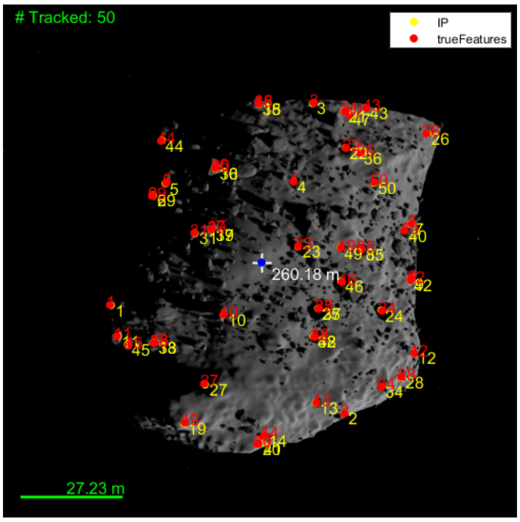

Figure 3: Tracked Features and LRF measurement for close range navigation at 300 m.

Relative navigation techniques based on features have been successfully implemented in a few asteroid landing missions, offering a reliable solution when GPS signals are unavailable. However, a purely relative solution has not yet been employed. Several missions, such as Hayabusa2, OSIRIS-REx, and MASCOT, have utilized feature-based navigation systems with either absolute or ground-based information. Hayabusa2 employed a Target Marker Navigation (TMN) system, where a target marker was deployed on the asteroid's surface and used as a reference point. OSIRIS-REx utilized Natural Feature Tracking (NFT) algorithms to identify and track prominent features from an absolute referenced database. MASCOT employed a stereo camera and onboard IP to navigate using surface features.
While these missions demonstrated the reliability and accuracy of relative navigation based on feature-based techniques, the pursuit of purely relative navigation remains at the forefront of SSSB and planetary explorations. Achieving pure relative navigation requires the utilization of advanced techniques such as Simultaneous Localization and Mapping (SLAM) and visual odometry. SLAM enables a spacecraft to create a map of its surroundings while simultaneously localizing itself within that map. This is achieved by employing sensors like cameras and LIDAR to measure distances and orientations of nearby objects. By combining sensor data with motion and dynamics information, SLAM algorithms accurately determine the spacecraft's position and orientation relative to the planetary surface. Visual odometry, another technique for relative navigation, tracks the motion of nearby objects using cameras to calculate the spacecraft's velocity and position relative to the target body based on changes in the visual scene. In our developments [9], a combination of SLAM and visual odometry techniques is utilized to achieve successful asteroid surface landing.
The derived solutions highlight the advantages of the novel extended Kalman filter (EKF) based on Simultaneous Localization and Mapping (SLAM). Firstly, the EKF-SLAM enhances observability of the line of sight by incorporating LRF measurements. This improved observability enables more accurate estimation of the spacecraft's position and orientation relative to the planetary surface, even in environments with limited distinguishable features. This capability is particularly valuable during the critical final stages of landing when high accuracy is crucial.
Secondly, the novel EKF demonstrates efficient use of features by reducing their number. This reduces the computational load of the algorithm, making it suitable for on-board implementation. The reduced number of features also leads to faster processing and improved reliability, as it minimizes opportunities for errors in feature detection and matching.
Additionally, the Monte Carlo analysis conducted on the filter demonstrates its robustness to boundary

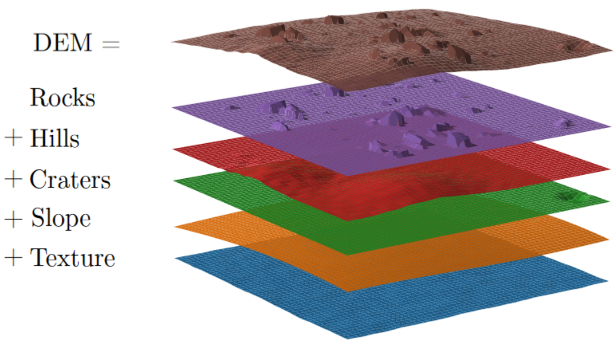

Figure 4: Environment generator from [11].

conditions, addressing unexpected obstacles or environmental conditions that may arise during space exploration missions. The filter's ability to handle such scenarios and maintain accurate estimates of the spacecraft's state further enhances its reliability and utility in space exploration missions.
Overall, the novel extended Kalman filter based on SLAM represents a significant advancement in the field of space exploration and autonomy. Its increased observability, efficient use of features, robustness to challenging conditions, and provision of relative estimated state for closed-loop guidance make it a highly promising technology for the future of space exploration.

4 DECISION-MAKING

The decision-making process consists of assessing the hazards from current sensor data and adjusting the trajectory if needed to avoid these hazards. Analogous to the environment perception, solutions based on camera and LiDAR data has been developed.

4.1 LiDAR-based Hazard Detection

One of the major challenges that can jeopardize a mission targeting the exploration of a celestial object is the landing. Finding safe landing sites requires the specification of the criteria constituting safety. Among others, criterias such as illumination conditions, slope, safety distance to obstacles and roughness must be considered. The environment is sensed as a sequence of point cloud measurements using flash-LiDAR sensors, and multiple scans are combined to obtain the representation of the terrain with enough level of details. They are then combined with Digital Elevation Maps (DEMs), that can be considered as "digital terrain models" providing 2.5-dimensional view of the surface.
A possible location of interest is heuristically selected (e.g. below current vehicle position, point ahead the current vehicle position) within the DEM and checked whether landing is possible or not. Therefore, critiera such as slope and roughness are estimated using Least Median Square (LMS) estimation method. The estimated information are combined with other information such as illumination conditions. Furhtermore, uncertainty in the gravity vectors and in the geometric map are faced. If the criteria fulfill pre-defined treshholds, the location of interest is marked as safe, i.e., location is a confirmed landing site. The functional architecture for landing site detection (LSD) in the Astrone project including uncertainties can be found in [11].
One disdavantage of the aforementioned method is the computation time. To alleviate the computational burden, a hybrid solution involving AI methods is suggested to leverage their speed and potential innovation while ensuring reliability using the aforementioned classical methods. The up-

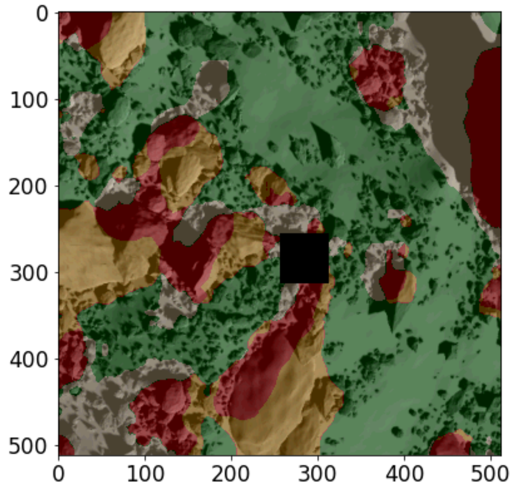

Figure 5: Safety Map and Original at 22.5 m from the surface, black square is the estimated lander footprint.

date with respect to the procedure just outlined is limited to the selection of the location of interest, replacing the previously used heuristic.

The approach uses the U-Net [12] to apply semantic segmentation with the goal of classifying hazards, where semantic segmentation is a computer vision task that involves labelling each pixel in an image with a corresponding class label, such as object classes, background, or parts of an object. The method uses an environment generator to generate datasets of DEMs with labels that combine roughness and slope into a hazard score for each cell. Labelled data is required to train the network, and the core idea of environment generator consists in building a DEM as superposition of different semantic layers, as shown in Figure 4.

The sematic segmentation step is used to quickly check whether or not a location of interest is suitable for landing. In other words, the sematic segmentation is used to quickly discard locations/areas that are unlikley to provide a suitable landing location. In case of a positive result from the segmentation the classical landing site detection procedure is used to check this location more accurately and to provide a reliable statement of the location of interest.

Finally, the robustness of the neural network is investigated and improved through transformations of the input, such as rotation and flipping of the images. Additionally, both a mean free noise to simulate the presence of distortions, and the stability loss term are employed.

Several improvements have been identified, including testing different architectures and optimizing for speed slightly over accuracy, but also addressing uncertainties around noise in map representation to increase the number of found landing sites.

4.2 AI-based LiDAR-free Hazard Detection

NEO-MAPP approach [13] integrates a single camera image with the measurement from the LRF, combining them to generate various safety maps directly associated with the landing criteria. These maps include factors such as the presence of hazards (e.g., large boulders), minimum illumination conditions, maximum allowable surface slope, proximity to the designated landing site, and minimum distance from unsafe areas. The solution aims to address the limitations posed by bulky LiDAR units and the lack of stereo baseline in small landers, which restricts depth resolution at the operational altitude range.

These autonomous hazard detection system operates without LiDAR, allowing for on-board selection of safe landing sites based on predefined requirements. The system is extensively tested and

validated on the μLander architecture, developed within the NEO-MAPP study framework [9]. This architecture serves as an ideal test case for achieving autonomous and secure soft landings on asteroid surfaces. Our innovative solution effectively combines machine learning (ML) techniques for hazard detection and slope estimation [14] with traditional IP, creating a hybrid workflow.
The Safe Landing Site Selection system we propose minimizes mass and cost, making it a pivotal technology for exploration missions that demand a high degree of autonomy. The algorithm we introduce offers essential functionalities for hazard detection and avoidance, as well as the autonomous selection of landing sites that comply with safety requirements.
In conclusion, achieving successful landings on SSSBs necessitates the implementation of autonomous and resilient lander systems. To enhance the autonomy of landing site selection, NEO-MAPP introduces the integration of supervised learning strategies into the hazard detection capability. Among various state-of-the-art semantic segmentation neural networks, the U-Net architecture is chosen as the optimal solution for hazard detection due to its superior accuracy, simplicity, and fast execution speed [14]. This architecture effectively identifies boulders without the need for extensive parameter tuning or long processing times. The resulting boulder map is further refined through post-processing techniques that consider prediction probabilities and surface distances, thereby increasing the safety of the risk map. The network's prediction capability demonstrates robustness across different illumination conditions, and the algorithms are validated using real mission images to qualitatively verify the results. It is important to note that the approach presented here focuses specifically on the assessment of safe landing sites and incorporates criteria related to illumination and boulder detection.
The presented framework introduces a novel approach to hazard detection and safe landing site selection, offering a lightweight and robust solution for micro-lander autonomy. By leveraging a hybrid pipeline combining machine learning and IP techniques, the framework is capable of extracting valuable information such as hazards and slope solely from the camera and LRF. This comprehensive fulfillment of stringent landing requirements is achieved while maintaining a limited mass budget, as it operates without the need for a LiDAR system. Furthermore, the solution features a small number of design parameters, enabling rapid tuning and facilitating efficient on-board implementation through high parallelizability. Importantly, the applicability of this innovative framework extends beyond SSSBs to include planetary landing scenarios.

4.3 AI-based Map Generation from Camera and LiDAR

Astrone navigation solution (Figure 1) provides the 3D surface map (extended DEM) that can be used for both hazard detection / avoidance and landing site selection. However, the limited resolution of the LiDAR sensor limits the resolution of the map and therefore the detection range. At the same

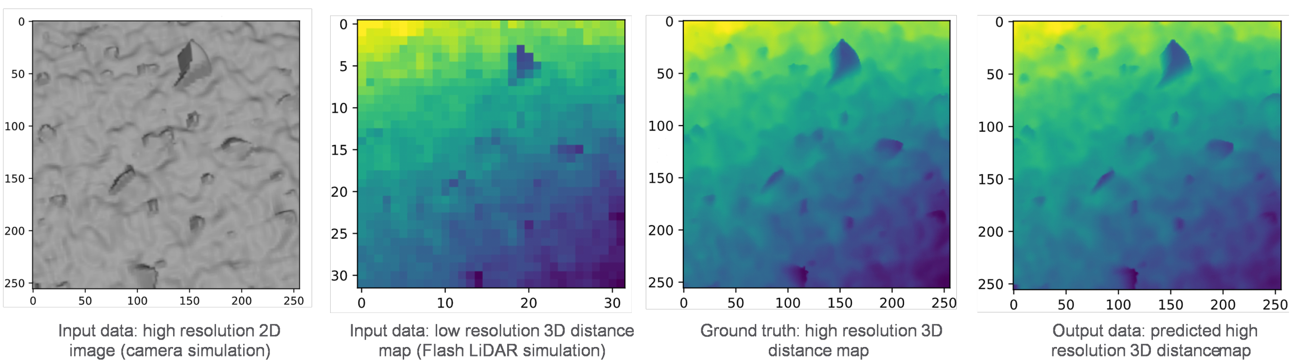

Figure 6: Example of validation results (in 3D distance maps local distances are represented by color).

time, a 2D navigation camera can provide several times higher resolution. Within a frame of currently running Astrone KI project, a solution for a high-resolution 3D terrain reconstruction by a deep learning-based fusion of coarse 3D data from low-resolution Flash LiDAR and high-resolution 2D imagery from a navigation camera has been developed.
The feasibility of the proposed solution has been demonstrated in initial tests using simulated close-up wide-angle asteroid imagery. As a result of AI-based data fusion with camera imagery, the resolution of Flash LiDAR 3D distance maps was successfully increased by a factor of 8×8 (Figure 6).
For the asteroid exploration mission, the results of the high-resolution 3D surface reconstruction will enable long-distance hazards / landing site detection. In addition, an AI-driven 2D image analysis solution is being currently investigated to pre-identify suitable landing sites from even greater distances.

4.4 Motion Planning to Explore Unknown Terrain

Exploring unknown or partially known environments is a challenging task for motion planning. In fact, complex environment involving changing of the terrain features from one region to another need to be considered in the generation of feasible and collision free trajectories. Moreover, both a high level of automation is required due to the distance from Earth and a small computational cost is necessary to run algorithms on space qualified hardware. A class of algorithms that can cope with these challenges are sensor-based. Such sensor-based planners have low computation times and do not require detailed maps of the environment. Trajectory generation relies only on the latest sensor measurement and hence allows to explore unknown environments. A 3D representation of the environment is acquired, e.g., point cloud data from flash-LiDAR sensors. At every sensor measurement, motion primitives are generated within the sensor field of view and checked for feasibility. The point cloud data is used to identify collision free motion primitives using a kd-tree data structure [15] and nearest-neighbor search algorithm [16]. Moreover, flights close to the surface are performed. To ensure close to surface flights while providing safety, a height corridor is assigned. Therefore, a surface height estimation based on LiDAR data is added to allow terrain following capabilities. In others words, the spacecraft automatically adapt it's flight path to the local terrain, stays in a pre-assigend height corridor and fulfills the vehicle limitations. Finally, the best motion primitive according to a cost function is selected. A more detailed description can be found in [17].
An example is depicted in Figure 7. The left part shows the flown trajectory with respect to the local surface. The blue star indicates the take-off location and the red star the pre-assigned target location. The flight path is actively adapted to stay in the height corridor. In the right part one can see that the vehicle stays in the pre-assigned height corridor for the complete flight.

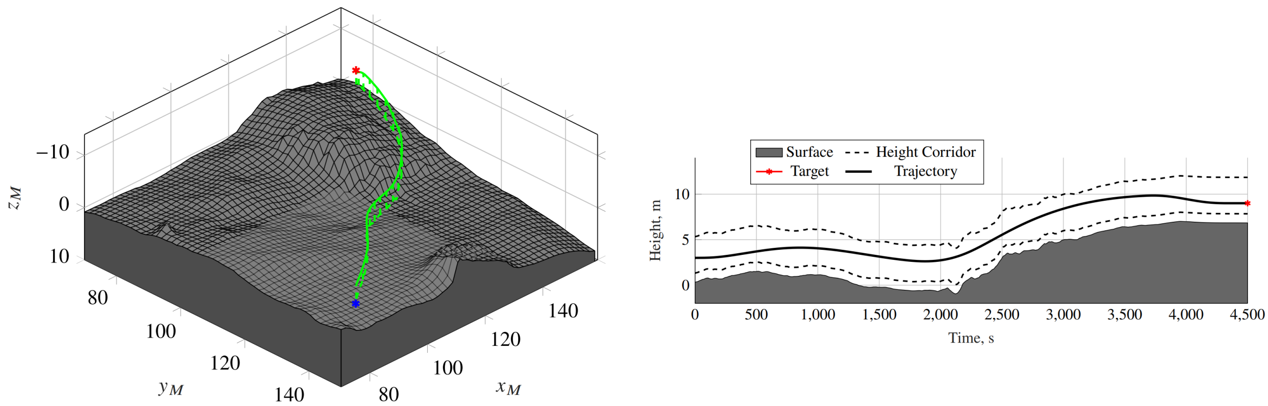

Figure 7: Example for terrain following capabilities. Figures taken from [17].

5 VERIFICATION AND VALIDATION TESTBED FACILITIES

All of the presented algorithms rely on the camera and LiDAR sensors. It is difficult to fully represent their realistic behaviour in simulators. For instance, synthetic images might not capture the real illumination conditions, and LiDAR simulators require on artificial surface models. Therefore, it is vital to test the GNC algorithms with real sensor data. The established and future verification and validation (V&V) testbed facilities are presented in the following.

5.1 Model-in-the-Loop

The first step in the V&V process is to devleop and test the autonomous GNC functionalities in a high fidelity model-in-the-loop (MIL) simulator. The simulator infrastructure from the Astrone project has been presented in [8]. The core part of the simulator is the camera and LiDAR generator. There is a large selection of software available such as PANGU [18], camera and LiDAR simulator (CamSim) from Astos Solutions GmbH [19], Blender [20], and SurRender from Airbus Defence and Space [21]. All of them require a shape model for the target body. This can be enhanced with additional features such as boulders and craters [8]. This setup allows assessing the sensitivity of the GNC algorithms for various surface conditions.

5.2 Processor-in-the-Loop

To test the computationally demanding algorithms (lower sampling frequency channel), a first preliminary processor-in-the-loop (PIL) setup has been created shown within the Astrone project as shown in Figure 8. It consists of one Windows PC for the execution of Simulink in real-time, one Linux computer for generating the synthetic camera and LiDAR data from the CamSim software delivered by Astos Solutions GmbH, and two Kontron board processors for the autonomous GNC functionalities (left side of Figure 8). All computers are connected via ethernet caple using TCP/IP interfaces (right side of Figure 8). The Simulink execution and the synthetic camera/LiDAR generator are seperated to reduce the computational load of each. There are two processors instead of one because of the concurrent design approach. The algorithms on the boards were developed independely at the two universities in Stuttgart (iFR) and Dresden (IfA). The remaining simulator such as the dynamics, kinematics, and environment (DKE) and control functionalities were provided by Airbus Defence and

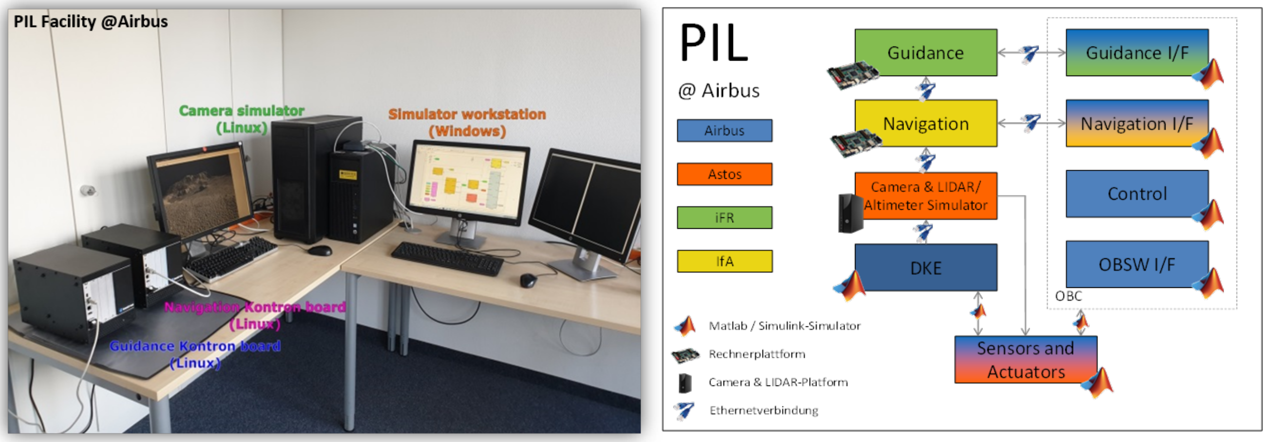

Figure 8: Final PIL facility at Airbus (left) and concurrent development plan (right).

Space GmbH. This preliminary PIL setup was used to assess the real-time capabilities of the algorithms and to demonstrate the employment of the algorithms on a processor. In the future, parts of the setup can be replaced by real sensors such as cameras and other processors.

6 CONCLUSION

The key to increased autonomous systems for SSSB scenarios is to fully exploit the information given by camera and LiDAR sensors. This would enable to launch probes to and around the surface of SSSBs without the need of extensive preparations from the ground. The presented solutions depend less on prior knowledge such as detailed shape models and require limited computational performance suitable for space applications. Additionally, AI-based solutions have been identified for specific functionalities, which could not be accomplished by model-based solutions or have to effciciently process the large data from the sensors. The algorithms have been tested on the MIL and PIL facilities to assess their robustness and real-time applicability. In the future, a more realistic testbed facility in form of a hardware-in-the-loop is necessary to replace the synthetic camera and LiDAR measurements with real units.

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