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KANARIA: IDENTIFYING THE CHALLENGES FOR COGNITIVE AUTONOMOUS NAVIGATION AND GUIDANCE FOR MISSIONS TO SMALL PLANETARY BODIES

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With the rapid evolution of space technologies and increasing thirst for knowledge about the origin of life and the universe, the need for deep space missions as well as for autonomous solutions for complex, time-critical mission operations becomes urgent. Within this context, the project KaNaRiA aims at technology development tailored to the ambitious task of space resource mining on small planetary bodies using increased autonomy for on-board mission planning, navigation and guidance.

This paper focuses on the specific challenges as well as first solutions and results corresponding to the KaNaRiA mission phases (1) interplanetary cruise, (2) target identification and characterization and (3) proximity operations.

Based on the KaNaRiA asteroid mining mission objectives, initially, a mission reference scenario as well as a reference mission architecture are described in this paper. KaNaRiA has been proposed as a multi-spacecraft mission to the asteroid main belt. Composed of a flock of prospective scout spacecraft, a mother ship carrying the mining payload and several service modules placed on a 2.8 AU parking orbit around the Sun, KaNaRiA intends to characterize main belt asteroid properties, identify targets for mining and perform a soft-landing for in-situ characterization and mining.

Subsequently, the autonomous navigation system design of KaNaRiA for the interplanetary cruise is presented. The navigation challenges, which arise in phases (1) to (3), are discussed. Particular attention is given to the sensor-technology readiness-level, accuracy, applicability range, mass and power budgets. In order to navigate in the vicinity of an asteroid, an information fusion algorithm is required that aggregates multi-sensor data as well as a-priori knowledge and solves the task known as simultaneous localization and mapping (SLAM). In order to deal with uncertain and inconsistent information and to explicitly represent different dimensions of uncertainty, a belief-function-based SLAM approach is used, which is a generalization of the popular FastSLAM algorithm.

The objective of the guidance task is the autonomous planning of optimal transfer trajectories according to mission driving criteria, e.g. transfer time and fuel consumption. Optimal control problems and the calculation of trajectory sensitivities for on-board stability analysis as well as real-time optimal control are explained.

Bringing cognitive autonomy to a spacecraft requires an on-board computational module as a central spacecraft component. This module is responsible for state evaluation, mission planning and decision-making regarding selection of potential targets, trajectory selection and FDIR. A knowledge-base serves as a database for decision making processes.

With the aim to validate and test our methods, we create a virtual environment in which humans can interact with the simulation of the mission. In order to achieve real-time performance, we propose a massively-parallel software system architecture, which enables very efficient and easily adaptable communication between concurrent software modules within KaNaRiA.

I. INTRODUCTION

Following the developments and the news on current space missions such as Rosetta or Dawn, one of the biggest challenges for small body rendezvous and landing missions is the large communication delay that leads to operational problems. Operations need to be planned thoroughly in advance. Nevertheless failures and anomalies often result in the complete loss of the spacecraft or lander. One approach to improve the reliability of complex operations is to enhance the autonomy, decision making and FDIR (fault, detection, isolation and recovery) capabilities of the spacecraft.

This is the approach that the project KaNaRiA takes up. The German acronym KaNaRiA stands for *Kognitionsbasierte, autonome Navigation am Beispiel des Ressourcenabbaus im All*, which translates into *Cognitive Autonomous Navigation for Deep Space Resource Mining.* As an interdisciplinary project, KaNaRiA focuses on autonomous mission planning, navigation and guidance in a-priori unknown environments dealing with the challenges of future space missions to minor planets. KaNaRiA strives to increase on-board spacecraft autonomy in the context of an asteroid mining scenario. The development of these concepts takes place in a virtual simulation environment, which serves as a test bed for a mission study. In this paper we give an overview of the KaNaRiA mission concept and the individual components of the system.

The paper is structured as follows. In section II and III, the engineering solutions applied to the particular mission scenario of KaNaRiA are presented, specifically the mission concept and reference scenario followed by the navigation system design and autonomous navigation concept.

Section IV covers the contribution of information fusion, which combines a-priori knowledge with sensor data to provide an information basis for autonomous decision-making.

In section V it is explained how the mathematical field of optimization and optimal control is used to calculate optimal interplanetary trajectories by solving infinite-dimensional optimal control problems.

In section VI the central component for on-board mission planning and autonomous decision-making is presented.

Section VII describes functionality of the simulation environment and its underlying software architecture.

II. MISSION: ASTEROID MINING

As an application for the proposed autonomous navigation, guidance and simulation solutions, an asteroid mining mission concept is defined.

The aim of asteroid mining opens up a huge space of scenarios and possibilities to implement a successful mission. The mission design changes depending on the desired resource, the purpose of usage or the location of the asteroid target. In order to specify a scenario, the JPL Rapid Mission Architecture [1] method has been applied.

II.I Mission Processes

The mission concept derivation is based on a separation and identification of processes that have to be fulfilled with the goal of mining a space body. First, the targets have to be mapped and characterized according to their natural resources and potential consideration for mining. These activities are done under the scope of Mapping, Characterization and Resource Determination (MCRD). Second, after having appointed a suitable target, the resource is mined by a separate miner (Resource Extraction and Exploitation, REaE). As an asteroid mining mission is by default a long-term mission, the transportation of the resources from the mining site to the refinery or designated user as well as the maintenance of the space elements involved have to be taken into account. Those activities are covered within the Maintenance and Logistics. For a more detailed description and definition of the mission, it is referred to Probst et al. [2]

As each of the processes involved in a successful mining mission imposes different requirements on the spacecraft architecture, separate spacecraft elements have been selected, each of them specialized for one specific process. The selection trade-off for each mission element architecture was done using a numerical method based on relative judgments with respect to suitable trade-criteria. The selection process is described in Probst et al. [2]

II.II Mission Elements

The following mission elements are involved in the mission scenario:

The *Potential Target Characterization Modules* (PTCMs) are in charge of exploring the considered targets in order to analyse their potential resource character.

The *KaNaRiA Miner Spacecraft* (KMS) lands on the designated target and excavates the resource.

The Refuel- and Repair- Elements (RF/RP) take care of the maintenance problems that occur.

An unmanned, autonomous *Operational Centre* (OC) serves as the main communication and delegation hub. It coordinates the mission elements and their tasks, sustains and collects the data and inherits the overall power of decision.

To complete the mining cycle, *resource transporters* are needed that carry the material from the mining site to the refinery or from there to the costumer.

II.III Mission Reference Scenario

As the mission scenario serves as a basis for the navigation, sensor fusion, guidance and autonomy algorithms and their implementation in a simulator, the mission scenario starts with a mission setup at a circular, Sun-bound parking orbit (2PO) with a semi-major axis of 2.8 AU. [2]

On 2PO, the OC, KMS and the maintenance spacecraft as well as the transporter are stationed whereas several PTCMs swarm out for their investigation and search for potential precious resources. Each PTCM consists of an orbiter and a re-docking lander so that it can visit more than one asteroid without coming back to 2PO. This way it is able to characterize each target thoroughly. The data obtained is relayed to the OC, which selects a definite target to which the KMS will head for mining.

In the simulator and further course of this project, the implementation and design will focus on the design of the PTCM as the developed technologies and algorithms can be transferred and applied to the other involved modules as well.

III. NAVIGATIONAL CONCEPT FOR DEEP SPACE MISSIONS

The KaNaRiA reference mission scenario envisages four main operational phases according to the mining processes described in section II.I: MRCD (Mapping, Characterization and Resource Determination), REaE (Resource Extraction and Exploitation), Maintenance and Logistics. Each of these phases imposes stringent performance requirements for the navigation subsystems of the various mission elements and their navigation autonomy capabilities. Within this section, the MRCD mission operations timeline is presented. The navigation requirements for PTCM spacecraft during the MRCD phase are discussed. The navigation system design of the PTCM is described and an autonomous navigation concept for interplanetary cruise is introduced.

PTCM Mission Operations Timeline

The operational concept for PTCM spacecraft is built upon the on-board autonomous capability for mission planning. Based on available system status information and collected knowledge about the target asteroid shape and dynamics, the spacecraft shall be able to select between 3 main concepts of operations while approaching an asteroid: an encounter mission and a lander mission with an additional option on red-coking the lander with the orbiter. The operational timeline for the scenarios is depicted in Fig. 1.

In an encounter mission scenario, the PTCM will perform remote sensing of the asteroid from a safe distance during a pre-planned time span. After finalization of the remote sensing campaign the PTCM will continue its course to a second target asteroid.

A lander mission scenario is selected if the asteroid target shows promising results after the remote sensing. The lander is released from the PTCM and uses its steering capabilities for safe landing on the designated landing site. The surface operations include a deep investigation of the asteroid's composition with a Low Frequency Radar as well as a Laser-Induced Breakdown Spectroscopy (LIBS) of the surface material. The data shall be relayed to the PTCM orbiter. The lander steering capabilities enable the performance of hopping or hovering manoeuvres between sample sites of interest. Additionally, the PTCM lander can ascent from the asteroid surface and re-dock to the PTCM orbiter in order to continue its course to a new asteroid. In case the PTCM delta-v capability is insufficient to perform a flight to a follow-up asteroid, the PTCM stays in the orbit around the asteroid and awaits - if profitable - the RF for refuelling.

The navigation system design of the PTCM spacecraft has been developed in order to ensure the spacecraft's capability to determine its location either absolutely in space or relatively to the target throughout all mission phases.

PTCM Navigation Requirements

The KaNaRiA mission concept proposes the deployment of 5-15 medium-size spacecraft, called PTCM, from a cargo control centre located in Sun-bound orbit about 2.8 AU distance from the Sun and 1.8 AU from Earth. At such distances, two-way ground-spacecraft communication delays exceed thirty minutes. Free-space transmission losses are as high as 290 dB in Ka-band, in which future deep-space communication

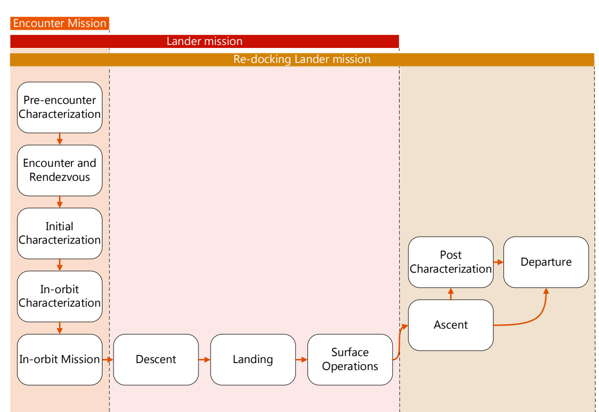

Fig. 1: Operational timeline (from left to right) for PTCM spacecraft,.

infrastructure will operate. The generation of sufficient power to frequently communicate with Earth for tracking purposes, while keeping all subsystems thermally conditioned and performing asteroid characterization operations is not a trivial problem given that the solar flux does not exceed 200 W/m^2. Furthermore, the simultaneous operation of 5-15 missions is a challenge for the already busy tracking and processing schedule of the deep-space ground infrastructure. It is therefore necessary to design the PTCM with a sensible balance between system complexity and self-contained autonomous navigation capabilities.

It has been determined that a PTCM shall be capable of performing on-board orbit determination (OD) at the 100 km precision during cruise in order to support guidance and control during orbit manoeuvring. OD shall be performed fully autonomously without ground support. The stability of the on-board solution shall be guaranteed for a transfer time as long as 4 years. OD updates from ground shall be expected regularly assuming a tracking campaign of maximum 1 week every 5 months.

The PTCM shall be targeted to a rendezvous-plane crossing point between 100 and 500 km from the asteroid surface depending of the volume sphere of influence of the particular object. The 3-σ error ellipsoid at rendezvous condition shall be constraint to 100 m – a requirement that has been fulfilled comfortably by previous asteroid fly-by missions.

During the asteroid in-orbit phase, a thorough characterization of the asteroid surface properties, internal structure as well as landing site selection and mapping will be carried out. During the observation campaigns a position accuracy in the order of meters relative to the asteroid surface shall be achieved.

The landing sequence will consist of a horizontal equalization phase and a subsequent vertical descent. The landing strategy has been designed to ensure soft landing (the survival of the PTCM lander structure), safe landing (safety of landing site avoiding obstacles bigger than 50 cm and slopes higher than 10 degrees) and hazard detection capability up to 10 minutes from touchdown.

Navigation System Design for a KaNaRiA PTCM

The PTCMs have been designed to perform inertial-aided optical navigation throughout all mission phases. In Table 1 a list of the navigation instruments has been provided including their type, mass and primary usage.

Cruise navigation

During cruise the angular observations of planet chords, star-planet and star-Sun angles are combined with the relative Doppler shift of the optical Sun spectra to derive spacecraft position and velocity. The self-

Instrument	Mass [kg]	Usage
Resonance Scatter Interferometer	42.2	Optical Sun Doppler observations
Coupled Star-Sun tracker	1.98	Stellar attitude and star-planet observations
Fine Sun Sensor	0.65	Coarse Sun attitude
Wide-Angle Camera	2	Asteroid detection and mapping
Narrow-Angle Camera	6	Surface mapping
Lidar Altimeter	3.52	Range finder
3D Lidar	6.5	Asteroid mapping
Space Inertial Reference Unit	7	Inertial position and attitude reconstruction

Table 1: PTCM navigation sensor suite

contained navigation approach is based on the method proposed by Guo [3] and further investigated by Yim [4].

Spacecraft attitude is reconstructed from the stellar attitude provided by star tracking and from the rate-gyro integration during manoeuvring. Coarse Sun attitude sensors are mounted as back-up solution.

Fig. 2 shows the power flux available from planetary emission and chord lengths of solar system planets in the optical bandwidth as observed by a spacecraft flying a sun-bound circular orbit at 2.8 AU.

Planetary atmospheric and surface albedo has been taken into account. The main selected bodies to be observed for navigation are the Sun, Jupiter and Earth. However other planetary bodies, including the targeted asteroid, are observed when illumination and geometry

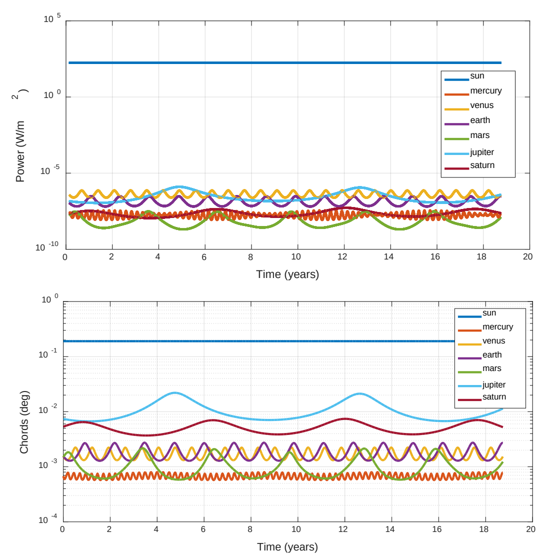

Fig.2: Power flux (top) and angular chord length (bottom) of Sun and solar system planets as observed from a Sun-bound circular orbit with semi-major axis of 2.8 AU.

conditions are favourable.

During cruise, Doppler frequency shift measurements from the Sun optical spectra are used to derive the spacecraft radial velocity. The derived radial velocity measurements are combined with planet chord length angles, planet-star and Sun-star angles. Angular measurements are processed according to standard celestial navigation procedures together with radial velocity measurements in an unscented Kalman filter. A particle filter is simultaneously executed in parallel with timely state updates from the Kalman filter. The particle filter (see section I.V) allows for a robust estimation in mismodelled dynamic environments, as for instance, the vicinity of an asteroid whose gravity field has not been probed. Fig. 3 illustrates the optical cruise navigation system of a PTCM spacecraft.

Optical navigation is aided by means of inertial measurements from the space inertial reference unit during orbit and attitude manoeuvring.

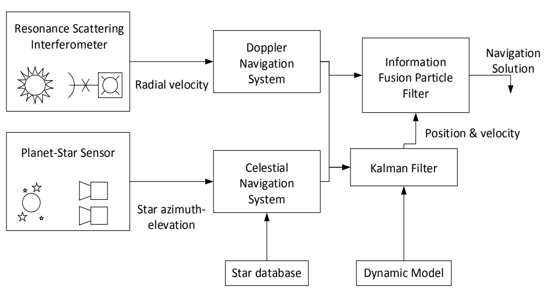

Fig. 3: Integrated celestial and optical Sun Doppler navigation system.

Asteroid relative navigation

In the vicinity of the target asteroid, optical navigation is implemented by means of feature tracking with two optical cameras and a 3D LIDAR. Visual SLAM (simultaneous localization and mapping) is used to reconstruct the asteroid shape and global map, and to locate the spacecraft relative to the generated surface map (see section I.V). A parallel estimation of both, spacecraft state and map, allows for increasing accuracy in the asteroid spin-state knowledge i.e., rotation axis orientation, rotation rate, tumbling modes, etc.

Star trackers are used for stellar attitude reconstruction as long as the asteroid covers between 60 and 80% of the instrument field of view. Rotation-rate measurements are collected from gyros to integrate attitude between stellar-blind phases and during the descent of the PTCM lander.

During descent, the PTCM lander uses a LIDAR altimeter to reconstruct height and vertical speed independently from the main SLAM navigation engine. The LIDAR altimeter solution is fed as input for the collision avoidance decision process handled by the on-board mission planning autonomy.

IV. MULTI-SENSOR FUSION FOR SPACE NAVIGATION

The information fusion subsystem aggregates multi-sensor data and a-priori knowledge to a unified representation, which serves as a basis for cognitive autonomous decision-making (Fig. 4). This bio-inspired model of decision-making relies on perceptions governed by top down as well as bottom up information flows. [5,6]

In particular, the aggregated information is comprised of *i)* top-down a-priori knowledge about the world and the spacecraft as well as *ii)* bottom-up perceived knowledge, which consists of fused data from multiple sensors. In conjunction, this information results in an estimate of the current spacecraft and environment state.

The multi-sensor fusion and state estimation solves the versatile challenges posed by the different mission phases (see section II) within one framework. Throughout all mission phases, a particle filter is used to approximate the desired probability distribution.

In the interplanetary cruise phase, the distribution $p(\boldsymbol{x}_t|\boldsymbol{z}_{0:t},\boldsymbol{u}_{1:t})$‡‡ over the current spacecraft state

$$\boldsymbol{x}_t = [\boldsymbol{r}_t^T, \boldsymbol{q}_t^T, \dot{\boldsymbol{r}}_t^T, \dot{\boldsymbol{q}}_t^T, \ddot{\boldsymbol{r}}_t^T, \ddot{\boldsymbol{q}}_t^T\ ]^T$$

given all measurements $\boldsymbol{z}_{0:t}$ and controls $\boldsymbol{u}_{0:t}$ is estimated in a heliocentric reference frame, where $\boldsymbol{r}_t$ is the position, $\boldsymbol{q}_t$ the attitude, $\dot{\boldsymbol{r}}_t$ the velocity, $\dot{\boldsymbol{q}}_t$ the angular velocity, $\ddot{\boldsymbol{r}}_t$ the acceleration, and $\ddot{\boldsymbol{q}}_t$ the angular acceleration of the spacecraft. $\boldsymbol{z}_t$ contains measurements from the interferometer, the coupled Sun-star tracker and the wide-angle camera (see section III).

In the MCRD phase, the camera suite and the mapping LIDAR are able to perceive the asteroid. This enables the multi-sensor fusion module to estimate a map Y of the approached asteroid. This provides a

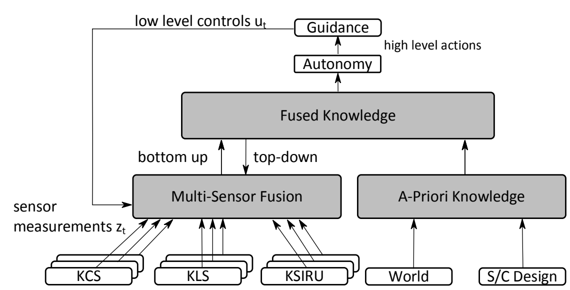

Fig. 4: Knowledge acquisition process for cognitive autonomous decision-making.

‡‡ For convenience reasons we use $\boldsymbol{a}_{0:t}$ as a short notation for a time series of variables $\boldsymbol{a}_0, \boldsymbol{a}_1, \dots, \boldsymbol{a}_t$.

physical description of the asteroid and, even more essential, can be used as a reference for relative spacecraft state estimation.

Although the two tasks of localization and mapping can be solved separately, they are not independent of each other. It is a joint estimation problem commonly known as Simultaneous Localization and Mapping (SLAM) [7] (Fig. 5). However, using a conditional independence assumption, the corresponding joint probability distribution can be factorized into one conditional distribution over the trajectory $\boldsymbol{x}_{0:t}$ and one over the map Y:

$$p(\boldsymbol{x}_{0:t}, Y|\boldsymbol{z}_{0:t}, \boldsymbol{u}_{1:t}) = \underbrace{p(\boldsymbol{x}_{0:t}|\boldsymbol{z}_{0:t}, \boldsymbol{u}_{1:t})}_{Trajectory} \underbrace{p(Y|\boldsymbol{x}_{0:t}, \boldsymbol{z}_{0:t})}_{Map}.$$

This allows us to use a technique called Rao-Blackwellization. [8] In the first step, the distribution over the trajectory is approximated by the particle filter [9] using controls, measurements and map estimate. In the second step, the current state is assumed to be known and the distribution over the map is computed analytically.

Initially, a landmark-based map is estimated in order to establish robust relative navigation in an asteroid-centric reference frame. The landmarks will be extracted by performing bio-inspired feature detection and description using Intrinsic 2 Dimensional (I2D) features [6,10] on the images obtained by the on-board cameras and with the distance information provided by the LIDAR instruments.

When the landmark map has full coverage and allows for a robust localization, it is extended by a belief-function-based grid-map of the asteroid in the proximity operations phase. It divides the volume into discrete grid cells where each grid cell represents an estimate of a corresponding piece of the physical environment. While the uncertainty regarding the true state is usually represented by a Bayesian probability, we are using belief functions [11,12] here, which allow to assign probability mass not only to the singletons $a \in \Theta$ of a hypothesis space Θ but also to all subsets of the power set $A \subseteq \wp(\Theta)$ including the superset Θ and the empty set $\emptyset$. This approach makes different dimensions of uncertainty explicit. E.g. a full lack of evidence is expressed by assigning all mass to Θ while conflicting evidence is expressed by mass assigned to $\emptyset$. In the Bayesian probability framework, both cases would result in an equal distribution and would be therefore undistinguishable. There are several works on mapping using belief functions [13,14,15] while a belief-function-based SLAM approach as a generalization of the successful grid-map based FastSLAM [16] algorithm was presented by Reineking and Clemens. [17] This approach was already applied in the context of extra-terrestrial exploration. [18,19]

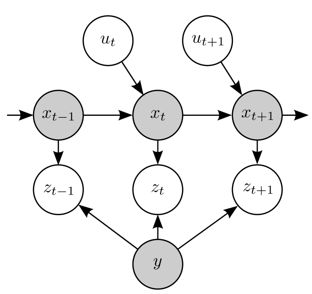

Fig. 5: Bayesian Network depicting the SLAM-problem.

The combination of belief functions and a grid map allow for *i)* a finer representation of the physical environment and *ii)* a better representation of the cognitive uncertainties. [20] This in turn enables the autonomy to pursue advanced exploration strategies to actively investigate possible landing sites, with respect to commodities, hazardous areas and fuel consumption. Based on the uncertainty information in the maps (grid-map as well as landmark based) the autonomy can be provided with desired actions with respect to every navigation instrument. Thus, particular actions can be assessed for their expected information gain.

V. OPTIMAL TRAJECTORY PLANNING

Trajectory planning for deep space missions is a topic of great interest. Mathematical fields like optimization and optimal control can be used to realize autonomous missions while protecting resources and making them safer. A perturbed *optimal control problem* (OCP(p)) has the form

$$\begin{aligned} \min_{x,u} F(x,u,p,t) &:= g(x(t_f),t_f) + \int_0^{t_f} f_0(x(t),u(t),t,p)dt \\ s.t. \qquad \dot{x}(t) &= f(x(t),u(t),t,p) \\ x(0) &= x_0 \\ \Psi(x_0, x(t_f), p) &= 0 \\ C(x(t),u(t),t,p) &\leq 0 \end{aligned}$$

with F being the objective function depending on the state $x(t)$ at time $t \in [0, t_f]$, the vector p describing model perturbations and the control function $u(t)$ by which the system's dynamic f can be influenced via differential equations. The control u has to be chosen in such a way that the constraints C as well as the initial and terminal conditions Ψ are fulfilled while minimizing the objective function F.

In principle, there exist two ways to solve an OCP(p), the so called indirect and direct methods. The indirect methods are being studied since several decades and need advanced skills regarding optimal control theory. Some algorithms are described in Bürlisch [21], Deuflhard [22], Ho and Bryson [23] as well as Miele [24]. The direct approach transcribes the infinite-dimensional OCP(p) into a finite-dimensional *non-linear optimization problem* (NLP(p)) via discretization of states and controls. [25,26] An NLP(p) consists of an objective function F and constraints G:

$$\begin{aligned} \min_{z} \quad & F(z,p) \\ s.t. \quad & G_i(z,p) = 0,\ i = 1,\dots,M_e \\ & G_i(z,p) \leq 0,\ i = M_e+1,\dots,M \end{aligned}$$

The objective function F depends on the optimization vector $z := (x_1^T, \dots, x_{N_t}^T, u_1^T, \dots, u_{N_t}^T)$ with $x_i, u_i, i = 1, \dots, N_t$ representing the former x and u at discrete time points $0 = t_1 < t_2 < \dots < t_{N_t} := t_f, x_i \approx x(t_i), u_i \approx u(t_i)$ and the perturbation vector p. For a fixed parameter $p = p_0$ an optimal solution is called the *nominal* or *undisturbed solution* indicated by $z(p_0)$.

The OCP(p) formulation's dynamic model describes the movement of the spacecraft due to main gravitational influences of the sun and other planets as well as the thrust commands through ordinary differential equations (ODEs):

$$\dot{x} := \begin{pmatrix} \dot{p}_{sc} \\ \ddot{p}_{sc} \\ \dot{m}_{sc} \end{pmatrix} = \begin{pmatrix} \dot{p}_{sc} \\ \sum_{i \in I} \mu_i \cdot \frac{r_i}{\|r_i\|_2^3} + \frac{T}{m_{sc}} \\ -\frac{\|T\|}{g_0 Isp} \end{pmatrix}$$

Herein p_{sc} is the position vector of the spacecraft, $\mu_i, i \in [Sun, Mars, Jupiter, Saturn]$ is the gravitational constant of the according celestial body and r_i the direction vector between spacecraft and body, $T = [u_x, u_y, u_z]$ is the thrust vector, m_{sc} the spacecraft's recent mass, I_{sp} its specific impulse and g_0 the gravitational constant of Earth.

Within the optimization there exist several methods to solve such ODE systems. One is the so-called full discretization, where all states and controls are calculated for a chosen number of discrete time points. An alternative is to use *multiple shooting methods*. Here the solution space is divided into several sections by so-called *multi-nodes* and for each section a *single shooting method* is applied. [27] It is sufficient to combine the sections by additional constraints in order to gain the correct solution in the end. In the KaNaRiA implementation the position of the multi-nodes is let free for optimization.

These methods will be investigated to achieve a robust and efficient optimization for each of the systemically different navigation phases of a space mission. The resulting non-linear high-dimensional optimization problems are solved using the software package WORHP [28] ('We Optimize Really Huge Problems'). This is especially efficient for solving high-dimensional problems like those resulting from the discretization of optimal control problems as it uses for example the sparsity information of the derivative matrices.

Additionally, an on-board-capable *parametric sensitivity* and *stability analysis* of optimal nominal solutions towards perturbations will be performed in KaNaRiA. Perturbations are for example deviations in the assumed amount of left over fuel, the magnitude of the solar pressure or the asteroid's gravitational influence, which may have a great impact on the practicability of a planned trajectory. Changes in the optimal solution of the undisturbed problem in case of deviating values p from nominal values p_0 can be estimated by calculating the solution vector

$$z(p) \approx z(p_0) + \frac{dz}{dp}(p_0)(p - p_0)$$

while only the nominal solution $z(p_0)$ and its sensitivities $\frac{dz}{dp}(p_0)$ need to be computed.

Whereas offline calculations of optimal trajectories allow for their investigation, a practical online-realization can only be achieved through special *real-time capable methods*. Based on the parametric sensitivity analysis and dependent on the different phases of a space mission and their special claims different trajectory optimization and real-time tracking strategies will be developed for differing time scales. When approaching the asteroid further and especially when entering the landing phase the challenges of efficient real-time capable control interventions increase due to the weak, inhomogeneous gravity field resulting from the relative small mass, irregular form and unknown rotation of the asteroid.

Implementation:

A simple way to achieve an orbit transfer is the Hohmann transfer orbit, but it is only applicable under strong constraints. That is why in KaNaRiA another approach was chosen. For the cruise phase a maximum of three thrust commands may be applied, one at the beginning of a trajectory, one at the end and one at an optimized time point in between. These commands are sufficient regarding the long time frame of the flight without serious perturbation forces. To model impulsive thrusting more accurately an application-adapted model is developed. By using the objective function

$$F = w_{tf} t_f - m_f (1 - w_{tf})$$

with t_f being the total flight time, m_f the spacecraft's final mass and $w_{tf} \in [0,1]$ a weighting factor where any fit between time- and energy-optimization can be chosen. The start mass of the spacecraft is 4000 kg, the fuel mass 1500 kg, the I_{sp} 318 seconds and the thrust is limited to 340 to 440 Newton. The optimization was performed considering the influences of the planets Mars, Saturn and Jupiter. The boundary condition was meeting the position and velocity of the asteroid within a certain range sufficient for the cruise phase. The solutions for full time and full energy optimization can be seen in Fig. 6 and Table 2. With 2157.56 kg of fuel consumption and a total flight time of 796.747 days the flight of the energy-optimal trajectory needs 125.55 kg of fuel less but 30.493 days longer than flying the time-optimal trajectory (Table 2). The energy-optimal trajectory contains two thrust commands whereas the time-optimal trajectory consists of three thrust commands in order to meet the objective. This way in order to meet the energy-optimal objective, the spacecraft might orbit on the original trajectory before thrusting for the first time. The changes in the z-position differs the most since changing the inclination of a trajectory is highly energy consuming. In comparison to the x-/y-positions, the thrusts lead to only a small adjustment in the z-position. For both trajectories the last thrust is applied at the end of the trajectory, whereas only the time-optimal trajectory has a thrust at the beginning of the manoeuvre (Fig. 6).

The solution trajectories show strong differences according to the chosen objective priorities which means being able to save a lot of mission time or fuel consumption according to the mission's needs and allowing for various and considerably different autonomous decisions.

VI. COGNITIVE SPACECRAFT AUTONOMY

The autonomy module is the central component for autonomous reasoning and decision-making regarding normal mission operation as well as emergency

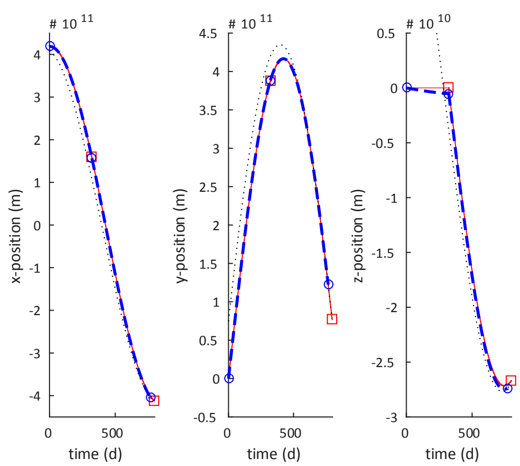

Fig. 6: X-, y- and z-position in meters of time-optimal (dashed blue line) and energy-optimal (solid red line) trajectory over time in days. The dotted black line shows the asteroid's position. Circles (time-optimal) and squares (energy-optimal) show the time points of the thrust commands.

	$w_{tf} = 0$	$w_{tf} = 1$	diff
Opt. criterion	energy	time	
Flight time (d)	796.747	766.254	30.493
Fuel (kg)	2157.56	2283.11	125.55
Line color (Fig. 6)	red	blue	

Table 2: Optimization criterion, flight time in days and fuel consumption in kg for two different mission trajectories.

situations. It controls all sub-modules of the spacecraft and all processes related to reasoning, plan generation, plan evaluation, plan execution and FDIR during all phases of the mission.

During normal mission operation, the autonomy module monitors both phase-specific mission objectives and the current state of the spacecraft. Based on these it generates plans to either achieve primary (e.g. locate the asteroid using optical sensors, maintain a stable orbit around the asteroid, perform the docking/landing operation) or secondary objectives (e.g. calculate alternative trajectory to further increase information on possible landing site). As the scenario is of a highly dynamic nature, the system periodically requests re-evaluation of plans to check whether they are still applicable. The appropriate strategy for re-evaluation is based on current system resources and time constraints. The autonomy module has to decide on and ensure commitment to one plan, yet retain the option to reconsider the commitment at a later point – when new information becomes available.

Uncertain knowledge resulting from incomplete or incorrect data poses a central challenge to reasoning and decision making, therefore the system has to consider these kind of uncertainties in the decision making process. Based on the biologically inspired principle of information maximization, the autonomy module seeks to minimize and resolve these uncertainties by employing information gain strategies and active perception to extend and improve the amount and quality of the available knowledge.

As autonomous handling of emergency situations is vital, the module utilizes FDIR algorithms to react to anomalies as they are detected, by reprioritizing primary and secondary mission objectives as well as planning and executing appropriate fault-detection, fault-isolation and fault-recovery plans.

Situation Analysis and Evaluation

To create a basis for decision-making and plan generation, the current state of the spacecraft and all information available to it has to be analysed and evaluated. This includes a-priori knowledge (spacecraft configuration, mission phase specific objectives), internal data (navigation variables, fuel, mass, health status) and external data (sensor measurements, asteroid properties, potential targets). Sensor information from optical cameras, an imaging LIDAR and a LIDAR altimeter are provided by the sensor fusion [5] to the autonomy module and combined to create maps that assign potentially hazardous areas, points of interest and potential landing sites to regions on the asteroid. In addition, boundary conditions for trajectory requests regarding different mission phases and actions are added.

Plan Generation, Assessment and Execution

During plan generation, the system decomposes high-level objectives into a sequence of actions. These are selected from a dynamic set of currently available actions and based on the current beliefs of the spacecraft. At the atomic level, actions can be executed by the spacecraft actuators, which include spacecraft propulsion, reaction wheel control, and communication with other entities, sensor control and deployment of other vehicles (PTCM orbiter and lander). As the environment is dynamic, objectives can become unachievable and thus plans can become obsolete. The autonomy must be able to assess whether a given plan is still feasible and react accordingly.

Attitude and Sensor Control

To fulfil phase specific mission objectives that require distinct sensor and actuator alignments, the autonomy module has to provide an attitude control sequence based on both proposed priority rankings of measurable information and communication requirements.

This attitude control sequence is based on a previously calculated trajectory, where a trajectory is represented as a sequence of positions and time points. This sequence is split into segments at the control points of the trajectory. For each of these segments a spacecraft orientation is calculated for which all available sensors potentially provide the best measurements with respect to the maximisation of gained information.

From these orientations along the trajectory, the required attitude controls can be determined. Taking into account the potential information gain and hazards along this path, a sensor control plan for the trajectory is calculated, which specifies the sensor activation and deactivation at all time points.

Autonomous FDIR

To enable the system to autonomously perform fault detection, isolation and recovery (FDIR), current knowledge about the spacecraft and the world is used to infer about possible erroneous states. Algorithms for anomaly detection are utilized to determine unusual world- or spacecraft state configurations (e.g. conflicting datasets, unusual high uncertainty) that indicate a hard- or software problem. These are analysed regarding fault-identification and fault-recovery. If available, information on error-models of sensors and probabilities for different error scenarios will be incorporated in this analysis. If one or more recovery strategies exist, the necessary actions to be performed and possible constraints on the further action selection and plan generation (e.g. an actuator ceased to function) will be evaluated. In addition findings of this analysis are provided to the sensor fusion to enable this module to adapt the corresponding sensor models accordingly.

VII. MASSIVELY PARALLEL AND PHYSICALLY-BASED SIMULATION

In this section, we highlight two key aspects of KaNaRiA's simulation software. First, we give an overview of our simulation software with a focus on its novel approach to concurrency control management. Second, we will present the challenges for our novel concept of gravity field simulation for irregularly shaped celestial bodies.

Realistic spacecraft simulations have to cover all aspects of a mission scenario in real-world detail. Internal spacecraft components, the space environment with its physical forces and disturbances, the sensor data acquisition chain, and the spacecraft actuator and propulsion systems have to be modelled and simulated.

One key aspect of such simulations is the validation and testing of specific performance aspects (e.g. navigation algorithms), enabling sophisticated analyses for engineers that would otherwise be impossible. These analyses (e.g. spacecraft landing procedure performance) require comprehensive simulation and the monitoring of vast amounts of generated data.

In recent years, simulation has emerged as a key technology for improving and streamlining the conceptualisation and design of vehicles by simulation in "virtual testbeds". [29,30] Virtual testbeds are constituted by a sophisticated physically-based simulation of both the vehicle and its designated environment, as well as real-time, immersive rendering and 3D interaction techniques. These testbeds give engineers the opportunity to interact with the simulated vehicle in order to gain comprehensive understanding of possible design flaws as early as possible during the design process. [29,31]

Consequently, the main challenge of such virtual end-to-end simulations for space missions is real-time simulation with highly responsive interactivity while maintaining realistic physical models. In this context, an enormous amount of software components is working in order to simulate both, spacecraft behaviour and required input data. Additionally, spacecraft engineers would, ideally, have the ability to easily manipulate parameters of the spacecraft(s), change aspects of space environment such as disturbances, add or remove sensors or other spacecraft components, and interactively test the spacecraft(s) under a variety of conditions.

In order to achieve the above stated software requirements, we have proposed and implemented the KaNaRiA virtual simulation (KVS) [32], which proposes an easily adaptable and customizable massively-parallel virtual reality system architecture with a centralized software infrastructure to attain real-time performance of the overall simulation.

Consequently, KVS enables the analysis and testing of autonomous spacecraft operation, spacecraft navigation algorithms, and spacecraft subsystems in an enriched, virtual world. It leverages physics-based spacecraft models in conjunction with high-quality, multimedia visualization and immersive interaction techniques to form an intuitive, accurate engineering tool.

KVS has been designed to take advantage of an open source game engine targeted at the video game industry. Thus, KVS is able to bridge the gap between traditional, high-fidelity analysis tools [33] and graphically realistic, immersive, and interactive simulations.

Some of the highlights of KaNaRiA's virtual simulation include:

- Real-time 3D rendering of complex space environments & spacecraft models
- Real-time simulation of spacecraft subsystems, sensors as well as actuators
- The ability to observe internal spacecraft data intuitively
- Controlled, repeatable testing for advanced simulations
- Intuitive and consistent user interface.

Rendering, internal multi-component spacecraft simulation, and interaction with the overall system happens completely in parallel in KVS. To avoid any latency between those parallel software components, KVS uses our novel concurrency control management (CCM) for wait-free data exchange, with its core being a global hash map, called key-value pool (*KVPool*, Fig. 7). [34,35] The KVPool is a centralized data storage that maintains the complete shared world state of the simulation without being a traditional, heavy-weight database.

Every simulation aspect, such as spacecraft subsystems, sensors, actuators, and any physical models are implemented as *entities*, which can access the KVPool. Other software components can access the data by simply passing the key to the KVPool. The wait-free behaviour of KVS's KVPool results in a dramatic speed-up of several orders of magnitude compared to traditional lock-based approaches (see Fig. 8), while

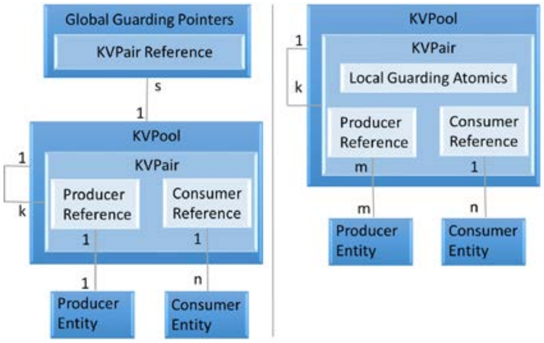

Fig. 7: Entity-relationship diagram of wait-free access to the shared simulation state by global guards (left) [34] and local guards (right). [35]

avoiding all their problems like deadlocks or thread starvation. Moreover, it overcomes the well-known many-to-many interface problem of the data-flow-based approach found in many traditional VR system architectures.

Furthermore, KVS's software infrastructure facilitates automatic code generation for virtual testbeds via domain specific modelling. [29] In addition, it can also be used for other data-driven simulation domains such as multi-agent-systems. [29]

Testing navigation and autonomous guidance algorithms for landing and orbiting an asteroid, under micro-g or milli-g gravity fields is crucial for developing fail-safe landing procedures. Therefore, KVS has to simulate a realistic gravity field around an asteroid for a given shape model (polygonal mesh) and density distribution at every point in space. We aim for fast and accurate computation of gravitational fields for any given asteroid. Currently spherical or ellipsoid harmonics approaches are the computationally least inexpensive compared with other approaches.

However, spherical harmonics series diverge within the Brillouin sphere [36] (see Fig. 9); hence, the gravitational field computed close to the surface of an asteroid is inaccurate. [37] This results in incorrect simulated gravitational forces acting on the spacecraft during landing phase.

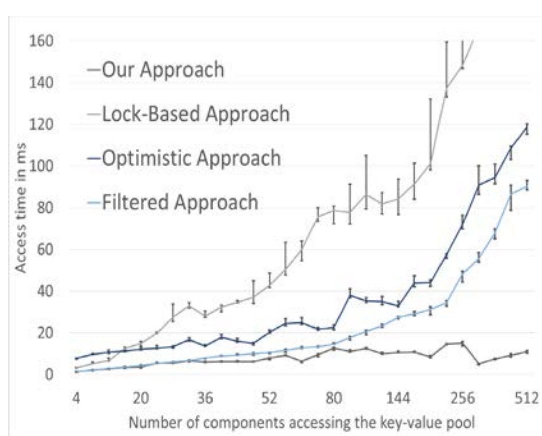

Fig. 8: Timings of a combined read and write operation for massively parallel access to a shared data structure.

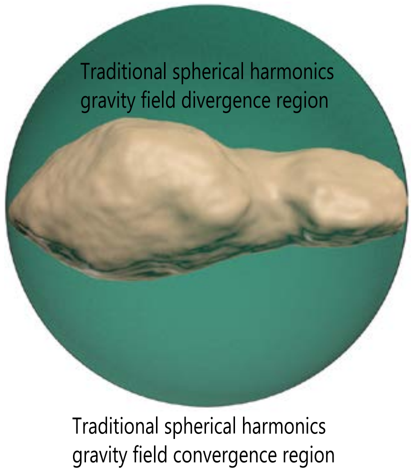

Fig. 9 : Brillouin sphere of asteroid Toutatis.

Takahashi et al. [38] overcame this issue with interior gravity field approach and alternatively with the interior spherical Bessel gravity field model. [39]

However, the former approach is computationally expensive as different sets of interior spherical harmonic coefficients have to be computed separately for each and every point on the asteroid surface, these different sets of coefficients are only applicable for gravity field computation within their respective interior sphere touching the respective point. [38] On the other hand, the pre-processing in the latter approach is computationally very expensive, which is not suitable for our purposes, since we need to be able to compute the field for any asteroid during runtime of the simulator. In our case, we generate the asteroids' shape models and density distributions procedurally in order to test guidance algorithms for landing on different types of asteroids (with respect to shape and density distributions) as well as sensor fusion algorithms for navigation. Therefore, we are currently working on an approach that computes the gravitational field of an asteroid in real-time while maintaining fast pre-processing. In our approach, we basically compute a sphere packing of a shape model of given asteroid using the modified protosphere algorithm from Weller et al. [39,40] with constraint on the radiuses of spheres based on the known prior asteroid density distribution. This method produces uniform density spheres that can be considered as point masses, then computing gravitational potential/acceleration at any given point is a trivial scalar/vector summation of potentials/accelerations applied by each sphere at that point (see Fig. 10). The sphere packing generation and summation computation for gravitational potential/acceleration are parallelizable. Hence, the pre-processing and gravity field computation are fast, which are suitable for our computational demands.

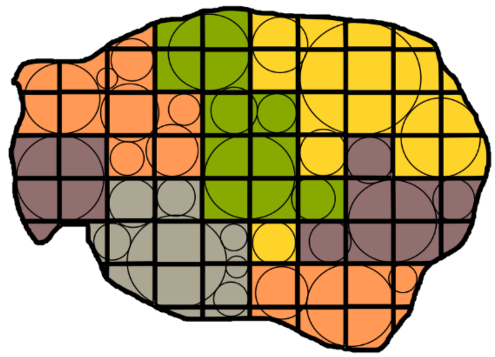

Fig. 10: Sphere packing of an asteroid with density distribution constraint on radius. The colours indicate different densities inside the asteroid.

VIII. CONCLUSION AND OUTLOOK

The KaNaRiA project focuses on the development of new autonomous decision-making, navigation, sensor fusion and guidance methods implemented on a virtual spacecraft. Within the spacecraft design, an autonomy module serves as the central controlling unit managing the data obtained and created by the navigation, fusion and guidance, generating and executing plans as well as controlling the attitude.

As an application for the development of this approach, an asteroid mining mission concept was developed. It considered asteroid mining as a long-term space activity. As the initial mission analysis led to the decision of a parking orbit located in the asteroid main belt, all involved mission elements need advanced autonomy strategies for navigation and guidance as well as mission planning and operations. During the KaNaRiA project, the design and application of the autonomous strategies focuses on the PTCMs consisting of an orbiter and a re-docking lander designed for a multi-rendezvous asteroid mission.

The navigation concept was designed for the PTCM operations timeline. It enables a thorough characterization of the asteroid surface properties as well as mapping including landing site selection with an envisaged position accuracy of several meters. The instrument suite to perform inertial-aided optical navigation under the imposed constraints by the mission concept was presented and the methods to conduct the observations were introduced. For cruise navigation, the navigation system design uses angular observation of planet chords combined with star-Sun relative Doppler shift to obtain the spacecraft position and velocity. The main selected bodies are Jupiter, the Sun and Earth with the option to consider other planets depending on their illumination conditions. The spacecraft radial velocity is calculated using the optical Doppler frequency shift measurement from the Sun and combined with planet chord length angles, planet star and Sun-star angles to determine position. The latter measurements are processed in an unscented Kalman filter whose results are used for timely state updates for the particle filter running in parallel. The Kalman filter ensures a robust estimation for mismodelled dynamic environments (e.g. vicinity of asteroids) such as an unprobed gravity field. For the purpose of relative navigation, two optical cameras and 3D LIDAR are used for feature tracking, optical navigation and independent height and vertical speed reconstruction during descent.

Based on the data obtained by the navigation sensor suite, the multi-sensor fusion subsystem provides all necessary information for cognitive autonomous decision-making. The data is obtained by a particle filter-based SLAM approach with a combination of a landmark-based map with a belief-function-based grid-map. The spacecraft dynamic state and the corresponding maps of the asteroid are estimated with a level of detail corresponding to the respective mission phase. This approach is applicable in every exploration scenario where an autonomous agent has to estimate its own position in an unknown environment and map it at the same time. Furthermore, the uncertainties encoded in the map enable an autonomous system to take cognitive decisions.

The challenge of finding the right interplanetary trajectory is solved using optimal control methods from the mathematical field. In KaNaRiA, the implemented approach allows a maximum of three thrust commands, one at the beginning, one at the end and one at an optimized time point in between. A weighting factor allows a customized fit between time- and energy-optimization. Using the optimal nominal solution as baseline, a parametric sensitivity analysis towards perturbations will be performed. Based on the parametric sensitivity analysis and according to the need for optimality, robustness and calculation time at hand, three real-time capable optimal control methods will be implemented: a method for model-predictive control (MPC), a method for repeated adjustment and an optimal feedback controller. Additionally, the approach of modelling the spacecraft motion will be applied to the task of navigation on the asteroid's surface to investigate an adaptive autonomous consideration of state-space constraints.

Analysing and evaluating the data obtained by navigation, fusion and guidance as well as other information available, the autonomy module assesses the current state of the spacecraft. The module acts as central component for autonomous reasoning and decision-making. The situation assessment is used as input for the decision on the feasibility of applicable mission objectives. Mission objectives are broken down into a sequence of actions, which are used to generate a plan. Due to a dynamic environment, the objectives could become unachievable depending on the spacecraft or environment state. With a changing environment, periodic requests of plan re-evaluations are necessary to either ensure commitment or reconsideration. The autonomy module also takes into account the uncertainty of the obtained knowledge using biologically inspired principles such as information maximisation and active perception. Finally, the execution of the plan is based on the trajectory optimization of the guidance subsystem. Using given time and control points, the actuators can be commanded. Based on the known attitude, a sensor control plan can be generated to specify their de-/activation schedule. Last but not least, erroneous states are inferred from the current knowledge of the spacecraft and world state utilizing anomaly detection algorithms for FDIR. All in all, the methods and algorithms developed in this project can be used to enhance the level of autonomy of future space missions with regards to navigation, plan generation, action selection and FDIR. The system provides the ability to represent uncertainty and incorporate this knowledge into the plan generation step. It can modify existing plans to include utility objectives aiming on reducing uncertainty and therefore enhances the robustness of the system with respect to unexpected situations.

The developed autonomy and navigation methods and algorithms are tested and verified in the KaNaRiA virtual simulator (KVS) using the mission scenario of asteroid mining as application. The KVS uses our novel concurrency control management approach with wait-free data exchange between various software components. A centralized data storage called KVPool is used, which resolves the many-to-many interface problem typically encountered in traditional VR architectures. This wait-free approach outperformed standard approaches in terms of access time as shown in the Fig. 8. The above software infrastructure can also be applied in other data-driven simulation domains. Currently, we are experimenting on a new approach for generating gravity field of asteroid shape models, which is based on sphere packing method [32]. This approach considers variable densities and overcomes the gravity field divergence problem in the Brillouin sphere region (see Fig. 9). However, at the same time our method also focuses on a fast computation of gravity potential and acceleration, and on fast generation of pre-processed data used for computing gravity fields.

The KaNaRiA project had its project kick-off in October 2013 and is designated for a period of four years.

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