Pages: 81- 89 / Vol. 17- No. 1 / **Winter- Spring 2024**

Journal of Aerospace Science and Technology

Journal Homepage: www:jast.ias.ir

Original Research Article

Optimal Path Planning of a Spacecraft via a Deep Neural Network for Soft Landing on the Irregular-Shaped 433 Eros Asteroid

Fahimeh Barzamini[1]*, Jafar Roshanian, Mahdi Jafari Nadoushan

1-2-3- Department of Aerospace Engineering, K. N. Toosi University of Technology, Tehran, Iran.

ABSTRACT

Article History:
Received: 31. October. 2023
Revised: 06. December.2023
Accepted: 09. December.2023
Available online: 01.June.2024

Keywords: *Online path planning, Deep Neural Network, Artificial intelligence, Spacecraft soft landing, Asteroid exploration*

DOI
doi.org/10.22034/jast.2023.423239.1168

This paper aimed to utilize a Deep Neural Network (DNN) to achieve optimal path planning for a spacecraft during a landing mission on an asteroid. A minimum energy-consumption mission is evaluated in which a DNN is utilized to predict the optimal path in case of any failures or unforeseen alterations. The paper uses a DNN and employs a polyhedral model, which is renowned as the most precise method for modelling the irregular shapes of asteroids. The DNN, is utilized for path planning and incorporates data calculated by the network into spacecraft's dynamics equations where an intelligent supporter model has been developed to handle the high computation load of the gravitational field of polyhedral models. Moreover, this study indicates that the prediction errors of final locations are less than 1 kilometer, as the training errors of networks are deemed entirely satisfactory. Eventually, the feasibility of the proposed approach is demonstrated through corresponding simulations.

Introduction

Asteroids are wandering space bodies with an asymmetric and irregular shape of stone or metal or stone and metal that move in different parts of the solar system and interstellar space. Most of them are located between the orbit of Mars and the orbit of Jupiter and revolve around the Sun, which is called the main asteroid belt. Another group of them are found elsewhere in the solar system, including at its outer edge, called the Kuiper Belt. Although more than 700,000 asteroids with approximate dimensions smaller than 1000 km have been discovered so far, only a small fraction of them have a modelable shape. So far, several asteroids have been observed and examined by radars or visited by spaceships in exploration missions, as a result of which accurate models have been obtained [1]. Spacecraft route planning has been discussed and studied as an active research topic in the space field in recent years. While most of the works are focused on 2D methods, 3D path planning approaches have been less researched. The development of commercial technologies and the progress of research make it possible for robots to appear in everyday life. For robots, one of the most basic and important abilities is path planning, i.e. autonomous path planning. This requires both time efficiency in responding to any emergency and safety in execution. Among the goals of path planning are moving from initial locations to target locations by autonomous operators and strategies, and maintaining security in preventing obstacles along the path. In 3D path planning of robotic systems, the goal is to find an optimal and collision-free path in a 3D workspace while considering movement limitations (including geometric, physical, and time limitations). The goal of path planning, unlike motion planning which is based on the dynamics of the problem, is to find an optimal kinematic path with minimum time as well as complete modeling of the environment. Many studies, especially in the last decade, have been

1 (Corresponding Author), Fahimeh Barzamini, Msc. Email: fbarzamini@mail.kntu.ac.ir

ISSN:1735-2134 Online ISSN: 2345-3648

carried out in order to solve some of the mentioned challenges and carry out missions around space stray objects. Among these studies, Yang and Baoyin solved a fuel-optimal control problem of soft landing on an irregular asteroid using an indirect method [2]. Their research has been followed to focus on the rapid generation of trajectory design of landing missions on an asteroid subject to time-optimal missions and other realistic constraints [3] [4] [5]. Pinson and Lu focused on rapidly design of a propellant optimal powered descent trajectory to land a spacecraft on an arbitrarily shaped asteroid, considering existent constraints of trajectory, thrust magnitude, and an applicable gravity model to these space bodies [6]. Xiangyu et al. studied soft landing on asteroids with an autonomous optical navigation and guidance algorithm that used image features of the asteroid surface [7]. Jiang et al. studied conventional path-planning tasks for a hopping rover to reach a known target on an irregular asteroid surface using a learning method [8]. Cheng et al. suggested a fast-solution for a time-optimal asteroid landing mission which was developed with a DNN solution to present a continuation approach to improve the autonomy and reliability of asteroid landing control [9-11]. Parmar and Guzzeti addressed a possible path-planning strategy in binary asteroid systems that applies to unknown dynamics and unreached environments such as asteroids [12]. Sakamoto and Kunii presented a novel hopping MDPs-Based Dynamic Path Planning algorithm for uncertain environments which can compute motion uncertainties and generate optimal actions [13]. In recent years, intelligent methods especially learning methods have played a key role in space mission design. Valenzuela et al. proposed a bio-inspired method to achieve a successful soft landing on the Near-Earth Asteroid (NEA) [14]. Rudin et al. employed deep reinforcement learning for legged robot missions in low-gravity environments [15]. Barzamini et al. extended their research on optimal path planning for a spacecraft fleet landing on an irregular asteroid which employed deep neural network and genetic algorithm [16]. Also, a number of researchers studied the application of the learning methods in space vehicles such as Tipaldi et al. which analyzes Reinforcement Learning (RL) based approaches to solve spacecraft control problems [17]. **Error! Reference source not found.** shows a flowchart of path replanning using DNN in an asteroid detumbling mission.

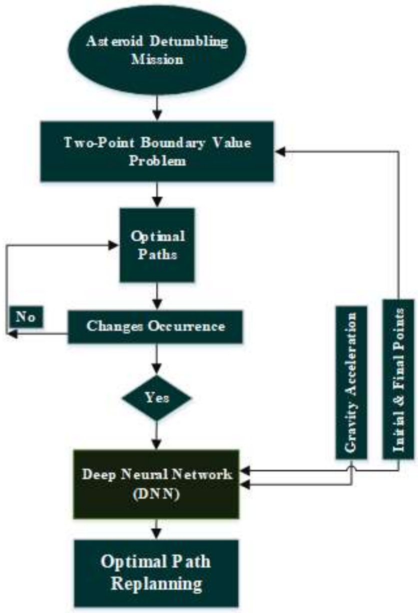

Fig.1 Flowchart of path replanning using deep neural network.

In this paper, we utilize a DNN to generate a minimum energy path to land a spacecraft on an asteroid while a failure or unforeseen alteration occurs. We used a polyhedral model, which is renowned as the most precise method for modelling the irregular shapes of asteroids, in combination with DNN for path planning. Results show the prediction errors of final locations are less than 1 kilometre.

Dynamic Modelling

Coordinate System

Asteroids usually have rotational motion. Therefore, due to the selection of the fixed body coordinate system of the rotating asteroid as the reference coordinate system, the rotational motion of the asteroid is considered to calculate the inertial acceleration. The gravitational potential field of an asteroid is a function of the position of the spacecraft in the body-fixed coordinate system of the asteroid, and therefore, the equations of motion of the spacecraft are defined in the body-fixed frame of the rotating asteroid. As shown in **Error! Reference source not found.**, $O_a - x_a y_a z_a$ indicates the fixed coordinate system of the asteroid, whose origin corresponds to the center of mass of the asteroid, its x_a axis is on the axis of minimum inertia, z_a in line with the axis of rotation of the object, and its y_a axis is set according to the right-hand rule. On the other hand, $O_b - x_d y_d z_d$ represents the body coordinate system of the spacecraft, whose origin is placed at the center of mass of the spacecraft. $O_l - x_l y_l z_l$ also indicates the coordinate system of the spacecraft landing place on the surface of the asteroid.

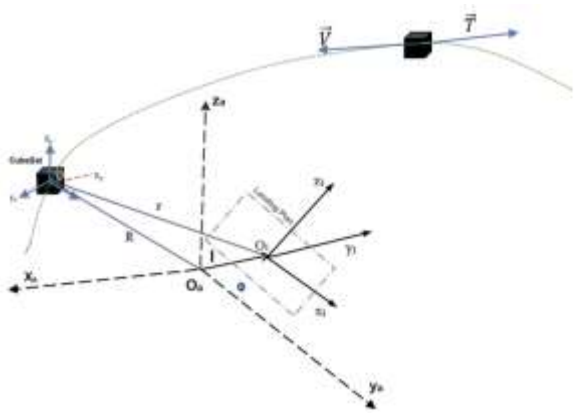

Fig.2 An overview of the coordinate systems of the asteroid and spacecraft.

The position vector of the spacecraft from the center of mass of the target asteroid in the fixed coordinate system of the asteroid can be represented by $R = [x. y. z]^T$ and is as follows:

$$\boldsymbol{R} = \boldsymbol{r} + \boldsymbol{\rho}. \quad (1)$$

here $\boldsymbol{\rho}$ shows the position of each landing point from the center of mass of the asteroid and $\boldsymbol{r}$ represents the position of the spacecraft from the landing point.

Motion Equations

The equations of motion of the spacecraft in the fixed coordinate system of a rotating asteroid with a constant rotation speed can be expressed as follows:

$$\ddot{\boldsymbol{R}} + 2\boldsymbol{\omega} \times \dot{\boldsymbol{R}} + \boldsymbol{\omega} \times (\boldsymbol{\omega} \times \boldsymbol{R}) + \dot{\boldsymbol{\omega}} \times \boldsymbol{R} = \boldsymbol{\nabla_R} \cdot \boldsymbol{U} + \boldsymbol{u} \quad (2)$$

where $\boldsymbol{\omega}$ represents the angular velocity of the asteroid. The first and second derivatives of the position vector relative to the fixed frame of the rotating body are denoted by $\dot{\boldsymbol{R}}$ and $\ddot{\boldsymbol{R}}$ respectively. $\nabla_{\boldsymbol{R}} \cdot U$ represents the gravitational potential gradient of the asteroid and $\mathbf{u} = [u_x, u_y, u_z]^T$ represents the control acceleration vector. To prepare for a soft landing on a target asteroid, a group of spacecraft must work together to control the asteroid's angular velocity to zero. To achieve this goal, once the spacecraft has landed at final point on the asteroid's surface, the thruster-equipped spacecraft will generate the torque needed ($\boldsymbol{\tau}$) to detumble the asteroid. Designing an optimal trajectory for spacecraft in a soft landing mission involves solving a two-point boundary value problem between equilibrium points (starting point) and landing points (endpoints) for each spacecraft. Focusing on the minimization of energy during flight the related equations can be presented as follows:

$$\begin{aligned}
\ddot{x} &= \boldsymbol{\omega}^2 x + 2\boldsymbol{\omega}\dot{y} + \nabla_R \cdot U_{\ x} + T_x + \delta u_x. \\
\ddot{y} &= \boldsymbol{\omega}^2 y - 2\boldsymbol{\omega}\dot{x} + \nabla_R \cdot U_{\ y} + T_y + \delta u_y. \\
\ddot{z} &= \nabla_R \cdot U_{\ z} + T_z + \delta u_z. \\
\dot{m} &= -\frac{1}{I_{sp} g_0} \|\mathbf{T}\| \qquad \|\mathbf{T}\| \leq T_{max}
\end{aligned} \quad (3)$$

In the following, an overview of the asteroid detumbling mission formulation is provided. At first, the related dynamic equations can be mathematically formulated in the framework of fixed body coordinates of the asteroid as follows [18]:

$$\dot{\mathbf{h}} + \boldsymbol{\omega} \times \mathbf{h} = \boldsymbol{\tau} \quad (4)$$

where $\mathbf{h}$ represents the angular momentum of the asteroid and $\boldsymbol{\tau}$, as mentioned earlier, is the torque produced by the cooperation of all the landed spacecraft. Analyzing equation (7) using the relationships between the inertia tensor, angular velocity, and angular momentum of the asteroid, we arrive at the following equation:

$$\mathbf{I}\dot{\boldsymbol{\omega}} + \boldsymbol{\omega} \times \mathbf{I}\boldsymbol{\omega} = \boldsymbol{\tau} \quad (5)$$

where $\mathbf{I}$ is the asteroid inertia matrix. As a result, the control of changes in angular velocity to reduce it to zero can be expressed in terms of its changes over time as follows:

$$\dot{\boldsymbol{\omega}} = \mathbf{I}^{-1}(\boldsymbol{\tau} - \boldsymbol{\omega} \times \mathbf{I}\boldsymbol{\omega}) \quad (6)$$

In addition, the optimal configuration of the landing sites for the group of spacecraft leads to the control torque required to reduce the angular velocity of the asteroid. This configuration is recalculated in case of any failure as well as changes in the number of available spacecrafts, and thus the final points of the trajectories are modified. We note that the focus of this paper is on replanning the optimal path in case of possible failures of a spacecraft using DNN in a resilient and autonomous mission context.

Usually, in space missions, they identify the most suitable landing points on the surface of an asteroid, assign them to each spacecraft, and plan the most efficient trajectories from the equilibrium points to these landing places. This approach minimizes the computational workload and execution time at the beginning of the mission. However, during the execution of the scenario in the real environment, uncontrollable events may cause the loss of some spacecraft, which makes it necessary to recalculate the optimal landing points on the asteroid surface and re-plan the optimal trajectories online and autonomously. This is a significant challenge, as new optimal paths have to be designed and part of the original mission has to be reprogrammed.

Initial and final points

Based on the first assumption, the asteroid's equilibrium points are considered as the starting point of the mission of landing on the surface which would minimize the force required to compensate the natural dynamics of the system. To make the designed mission feasible, first, the gravitational field of the selected asteroid was modelled using the polyhedron model and detailed real data collected from the asteroid 433 Eros by the Database of Asteroid Models from Inversion Techniques (DAMIT) (DAMIT, n.d.). In this regard, a polyhedral model including 25350 vertexes and 49152 faces is employed for the target asteroid modelling which is one of the most accurate models for irregular shapes like asteroids, and comets [19]. Then, by using the spacecraft motion equations (9) and equilibrium point equations (22), the unstable equilibrium points of the selected asteroid have been calculated according to Table 1:

Table 1. Equilibrium points of the target asteroid [20].

Equilibrium Points	x (km)	y (km)	z (km)
E1	19.1656	-2.6494	0.1414
E2	-19.7422	-3.3830	0.1278
E3	-0.4575	-13.9529	-0.0740
E4	0.4866	14.7123	-0.0627

To determine these points, a simplified mass model of the asteroid is needed. The dynamics used in this search is the gravitational force of the asteroid as well as the side force of the center of rotation rate of the stationary body frame of the asteroid relative to the inertial reference frame. In the following, by simulating the initial positioning of the spacecraft in the equilibrium points, their initial position is defined. Fig 1 shows the position of the equilibrium points of asteroid 433 Eros in the simulation.

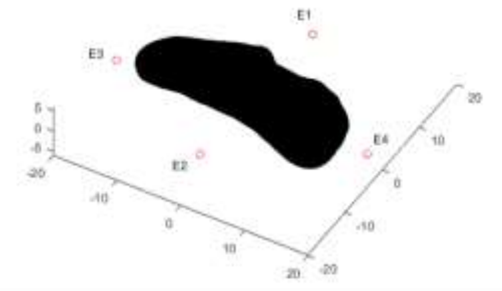

Fig 1. Equilibrium points of the 433 Eros asteroid.

Strategy of the Estimation of Near- Optimal path

Sample Data Generation

Generating sample data is the first step in network training, the accuracy of which is a fundamental rule in achieving reliable results. For this purpose, we try to collect a relatively large dataset of pairs of two distinct sets around the target.

Therefore, a cone-shaped region with an edge of 10 km is considered, which includes variable radii throughout reaching its apex. Fig 2 depicts an example of this distribution of data around the target asteroid to generate a dataset for optimal path prediction models as an external DNN. In this regard, optimal routes from different starting points to landing on the asteroid's surface are planned. The figure shows that the data are distributed in a cone of variable radius around the target asteroid.

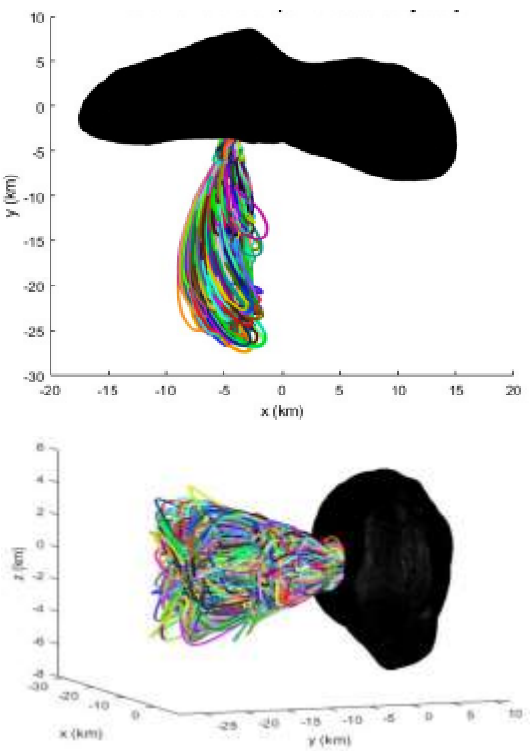

Fig 2. Sample data generated for the deep path planner network (2D & 3D view).

Fig 3 represents the successful results of the trained network. The set of network configuration variables is tabulated in Table 2.

Table 2. Network configuration variables

Parameter	Selection
Activation function	Output layer: ReLU
Hidden layer	Hidden layers: ReLU
Unit size/ Alpha	2
Initial LR	0.0001
Batch size	0.001
Training algorithm	5000
Error criteria	lbfgs Mean Square Error (MSE)

The successful development of the deep learning network has enabled accurate estimation of the gravitational field, ensuring proper performance of the network [28]. Fig 3 presents the training accuracy. In the context of activation functions for hidden layers, ReLU [0,1] and Tanh [−1,1] are commonly used. However, in this particular approximation task, ReLU has been found to outperform and therefore utilized in the hidden layers. The linear regression charts of the target and predicted values show that the external DNN development is done successfully. Also, the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) of the outer network demonstrate an acceptable accuracy which is presented in Fig 3.

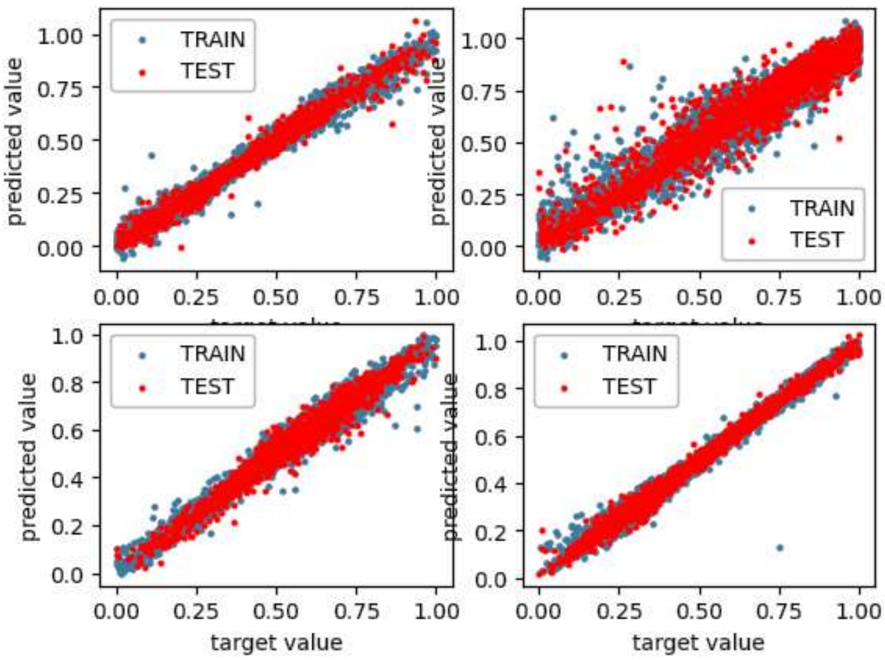

Fig 3. Network training results.

The quantitative analysis of the network approximation errors of the path equation is further depicted in Table 3. This table represents the approximation errors of the developed DNN for optimal path planning. These statistics are calculated using all the training datasets and the test dataset. As we can see from the table, the relative train and test approximations errors stay smaller than 5.521e-3. Taking these analyzes into account, it can be inferred that the trained control DNNs possess a remarkable level of accuracy in approximating optimal actions, making them a viable option for achieving real-time, optimal control during asteroid landing missions.

Table 3. Errors in the equation parameters

	Parameters	Mean Square Error	
		Train	Test
u_x	P_1	3.862e-4	4.721e-4
	P_2	2.652e-3	3.341e-3
	P_3	6.135e-4	7.352e-4
	P_4	3.224e-4	3.145e-4
u_y	P_1	1.201e-4	1.925e-4
	P_2	1.378e-3	1.882e-3
	P_3	1.322e-4	1.743e-4
	P_4	1.448e-4	1.901e-4
u_z	P_1	2.435e-4	4.095e-4
	P_2	3.514e-3	5.521e-3
	P_3	5.261e-4	5.024e-4
	P_4	4.133e-4	4.201e-4

Simulation and Results

The procedure outlined in the previous sections will be analyzed through a mission simulation. It is assumed that a spacecraft has a landing mission on the 433 Eros. In case of any failure that has occurred, a trained DNN including a 25000 dataset is employed to replan optimal trajectories from a new initial position to the specified landing locations on the asteroid's surface. The proposed method has gained brilliant results in both time reduction and speed of system operation enhancement. In this paper, a 20-core Intel Xeon gold 6226 CPU2.90 with 32GB Memory RAM and 500GB Hard Storage is employed for 25000 paths data generation. Python due to its high accuracy is used for the DNN training and MATLAB simulations using a 2.40-GHz Intel Core i5 processor are performed for the results extraction in simulation.
In the following, the spacecraft is assumed as a thruster as equipped with. In this regard, the landers' initial parameters are given in Table 4.

Table 4. Initial parameters of the spacecraft.

Parameter	Value
I_{sp}	225 s
T_{max}	60 N
r_0	E_3(Table 1)
M_0	1200 kg
v_0	$[0 \quad 0 \quad 0]^T\ m/s$

So far, important exploration missions have been carried out on the 433 Eros asteroid due to its asymmetric shape and relatively large size. Also, research has shown that this type C stony asteroid was discovered as the first asteroid and the second-largest near-Erath object that has rich resources of mineral elements. To attain the utmost precision in modeling the target asteroid, authentic data collected by probe spacecraft has been incorporated. The parameters of the target asteroid with a rather large dimension and irregular shape are given in Table 5.

Table 5. Asteroid parameters.

Parameter	Value
Mass	(6.687±0.003) e15 kg
Density	2.67 g/cm^3
Dimension	34.4 × 11.2 × 11.2 km
Angular Velocity	3.31458761013812e-4 rad/s

In this paper, we consider two flight scenarios in simulation to evaluate the performance of the proposed method, which is critical to prevent mission failure caused by inaccurate mission completion. The first flight is located in the natural equilibrium point of the target asteroid with zero velocity. However, the DNN-based algorithm successfully reduces the propagated error and keeps the trajectory deviation within acceptable limits. The second flight case is considered in somewhere in the middle path where a failure would make a necessary to optimal path replan. The optimal trajectory for each agent is replanned as follows:

a) Scenario: Soft Landing on Asteroid 433 Eros (Case a)

In this case, we consider that the spacecraft landing mission started from a natural equilibrium point of the target asteroid with a zero initial velocity. First, the spacecraft parameters are used as Table 4 as long as the initial and final position and velocity are tuned as follows:

$$
\begin{aligned}
r_0 &= [-0.4575, -13.9529, -0.074]km \\
\mathrm{v}_0 &= [0,0,0]\ \mathrm{m/s} \\
r_f &= [-0.968, -3.450, 0.613]km \\
\mathrm{v}_f &= [0,0,0]\ \mathrm{m/s}
\end{aligned}
\tag{7}
$$

As Fig 4 shows the control history of the minimum energy consumption path is predicted by the DNN in three control direction components. Setting $t_f = 1377.376\ s$, the results for energy optimal path is obtained through the developed nested DNN.

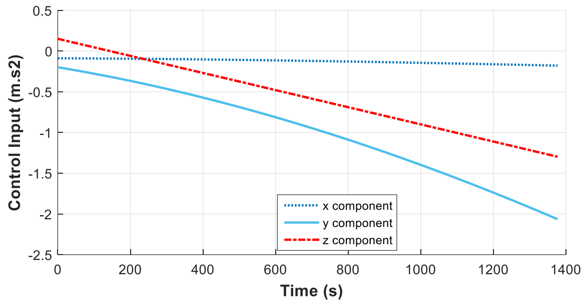

Fig 4. Predicted required control command for new optimal path (case a)

Figures confirmed the network approximations accuracy to the optimal and fast solutions which are the main factors of the developed DNN-based algorithm performance through introduced time-to-go t_f. Overall, these results demonstrate that the DNN-based controller can effectively reduce propagated errors and maintain accurate trajectory tracking during asteroid landing flights. However, it is essential to continuously monitor and adjust for any approximation errors to ensure safe and successful landings. Figure 5 demonstrates the optimal path predicted by the developed DNN from the asteroid's equilibrium point to a landing site on the surface. The red dotted line is the predicted path by the DNN while the blue solid line is the optimal path which is calculated by solving two boundary value problems (TBVP). The figure clearly illustrates that the predicted path exhibits minimal deviation from the optimal path. This suggests that the predicted path is highly accurate and reliable in terms of predicting the most efficient route. Furthermore, this finding highlights the potential benefits of utilizing such predictive models in various applications, including transportation planning and logistics management.

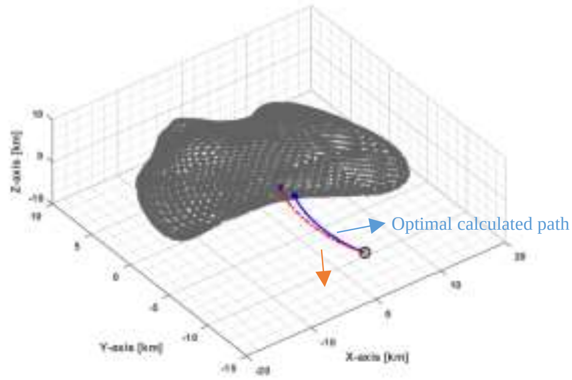

Figure 5. Predicted optimal path using DNN (case a).

b) Scenario: Soft Landing on Asteroid 433 Eros (Case b)

In this case, we consider an initial point in the middle of the optimal planned path which could be assumed as a new initial and final point where the spacecraft trajectory changed. This path replanning could happen because of any change in the final destination. It is obvious that in this case, the initial velocity is not equal to zero as well as the landing point is changed. In this regard, the initial and final boundaries condition is used as follows as spacecraft parameters are the same as the previous scenario.

$$
\begin{aligned}
r_0 &= [-3.8937, -23.0545, 3.4209]km \\
\mathrm{v}_0 &= [1.0418\mathrm{e}-3, 2.4183\mathrm{e}-3, 2.9437\mathrm{e} \\
&\quad -3]\ \mathrm{m/s} \\
r_f &= [4.050, -3.576, 0]km \\
\mathrm{v}_f &= [0,0,0]\ \mathrm{m/s}
\end{aligned}
\tag{8}
$$

Same as the first scenario, the control history plot as the errors of the second scenario is presented in Fig 6.

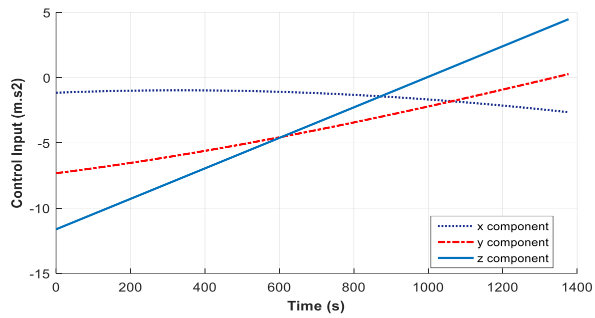

Fig 6. Predicted required control command for new optimal path (case b)

Fig 7 demonstrated the optimal path replanned by the developed DNN from a point somewhere in the middle of the previous path to a landing site on the surface. Same as the first scenario the red dotted line and blue solid one are representatives of the predicted and calculated paths by the DNN and TBVP, respectively.

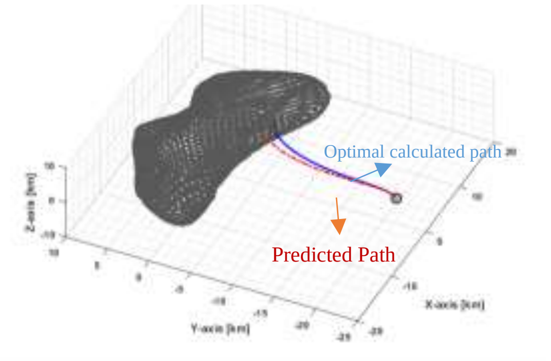

Fig 7. Predicted optimal path using DNN (case b).

The performance of the second scenario is a sign of algorithm robustness in path replanning where any failure occurs in the mission. As we mentioned, the difference between this scenario from the first one is introducing the initial boundary conditions of the agent in the path replanning problem. In this case, due to that the spacecraft is in its past optimal path, the velocity is not around zero.

As can be seen by the figures, the developed nested DNN is capable of driving the spacecraft to the target asteroid in an optimal manner whenever any unpredicted changes occur in position, velocity, and number of agents. The above two introduced scenarios with less than 1-kilometer error for the touching of final locations, further verify the performance of the proposed solution using DNN while reducing the time and burden computational of a complicated algorithm.

Conclusions

Optimal path planning has always been one of the most important and challenging issues of autonomous systems. Using intelligent methods in this field has been able to significantly increase their capabilities by improving the speed of trajectory design algorithms. On the other hand, the use of autonomous systems in many missions, especially space missions, has been able to expand human discoveries to the farthest exploration of the universe. Designing the optimal path using deep learning networks for landing a spacecraft has led to an increase in the speed and reliability of space missions so that the network will be able to re-estimate the optimal path in the shortest possible time in case of any required and unpredictable changes. In this paper, to train the network, a set of 25,000 data sets of estimated optimal routes has been produced. To verify the validity of the proposed method, two cases have been proposed in such a way that two starting points are considered: the first is from one of the equilibrium points of the target asteroid (original path) and the other is from a point in the middle of the previous (original) trajectory, which leads to re-estimation of a new and different optimal path. The simulation results have shown high accuracy in network training and are acceptable in estimating the new optimal path for both suggested starting points, “case a” and “case b”. Also, the proposed algorithm can reduce the computational burden of the optimal path planning process which could make serious mistakes due to delay occurrence in such sensitive missions. This field requires the expansion of research to increase the accuracy of the algorithm as much as possible, as well as its generalization and expansion to other missions, which are in the research program of these authors. Undoubtedly, the development of intelligent learning algorithms can help to increase the capability of autonomous systems in all applications, especially space missions.

Acknowledgments

The authors wish to thank anonymous reviewers for the fruitful and productive comments that has lift the quality of work significantly.

References

[1] Lincoln NK, Veres SM, Dennis LA, Fisher M, Lisitsa A. Autonomous asteroid exploration by rational agents. IEEE Computational Intelligence Magazine. 2013 Oct 17;8(4):25-38. https://doi.org/10.1109/MCI.2013.2279559

[2] Yang H, Baoyin H. Fuel-optimal control for soft landing on an irregular asteroid. IEEE Transactions on Aerospace and Electronic Systems. 2015 Jul;51(3):1688-97. https://doi.org/10.1109/TAES.2015.140295

[3] Yang H, Bai X, Baoyin H. Finite-time control for asteroid hovering and landing via terminal sliding-mode guidance. Acta Astronautica. 2017 Mar 1;132:78-89. https://doi.org/10.1016/j.actaastro.2016.12.012

[4] Yang H, Bai X, Baoyin H. Rapid generation of time-optimal trajectories for asteroid landing via convex optimization. Journal of Guidance, Control, and

Dynamics. 2017 Mar;40(3):628-41. https://doi.org/10.2514/1.G002170

[5] Yang H, Bai X, Baoyin H. Rapid generation of time-optimal trajectories for asteroid landing via convex optimization. Journal of Guidance, Control, and Dynamics. 2017 Mar;40(3):628-41. https://doi.org/10.2514/1.G002170

[6] Pinson RM, Lu P. Trajectory design employing convex optimization for landing on irregularly shaped asteroids. Journal of Guidance, Control, and Dynamics. 2018 Jun;41(6):1243-56. https://doi.org/10.2514/1.G003045

[7] Xiangyu H, Hutao C, Pingyuan C. An autonomous optical navigation and guidance for soft landing on asteroids. Acta Astronautica. 2004 May 1;54(10):763-71. https://doi.org/10.1016/j.actaastro.2003.09.001

[8] Jiang J, Zeng X, Guzzetti D, You Y. Path planning for asteroid hopping rovers with pre-trained deep reinforcement learning architectures. Acta Astronautica. 2020 Jun 1;171:265-79. https://doi.org/10.1016/j.actaastro.2020.03.007

[9] Cheng L, Wang Z, Song Y, Jiang F. Real-time optimal control for irregular asteroid landings using deep neural networks. Acta Astronautica. 2020 May 1;170:66-79. https://doi.org/10.1016/j.actaastro.2019.11.039

[10] Cheng L, Li H, Wang Z, Jiang F. Fast solution continuation of time-optimal asteroid landing trajectories using deep neural networks. Acta Astronautica. 2020 Feb 1;167:63-72. https://doi.org/10.1016/j.actaastro.2019.11.001

[11] Cheng L, Wang Z, Jiang F, Li J. Fast generation of optimal asteroid landing trajectories using deep neural networks. IEEE Transactions on Aerospace and Electronic Systems. 2019 Nov 11;56(4):2642-55. https://doi.org/10.1109/TAES.2019.2952700

[12] Parmar K, Guzzetti D. Interactive imitation learning for spacecraft path-planning in binary asteroid systems. Advances in Space Research. 2021 Aug 15;68(4):1928-51. https://doi.org/10.1016/j.asr.2021.04.023

[13] Sakamoto K, Kunii Y. A MDPs-based Dynamic Path Planning in Unknown Environments for Hopping Locomotion. IEEE Access. 2023 Jul 3. https://doi.org/10.1109/ACCESS.2023.3291401

[14] Valenzuela R, Flores-Abad A, Everett LE. A Bio-inspired Method to Achieve a Soft Landing on an Asteroid. In2018 AIAA SPACE and Astronautics Forum and Exposition 2018 (p. 5365). https://doi.org/10.2514/6.2018-5365

[15] Rudin N, Kolvenbach H, Tsounis V, Hutter M. Cat-like jumping and landing of legged robots in low gravity using deep reinforcement learning. IEEE Transactions on Robotics. 2021 Jun 14;38(1):317-28. https://doi.org/10.1109/TRO.2021.3084374

[16] Barzamini F, Roshanian J, Jafari-Nadoushan M. Optimal path planning of spacecraft fleet to asteroid detumbling utilizing deep neural networks and genetic algorithm. Advances in Space Research. 2023 Oct 15;72(8):3321-35. https://doi.org/10.1016/j.asr.2023.06.043

[17] Tipaldi M, Iervolino R, Massenio PR. Reinforcement learning in spacecraft control applications: Advances, prospects, and challenges. Annual Reviews in Control. 2022 Aug 18. https://doi.org/10.1016/j.arcontrol.2022.07.004

[18] Bazzocchi MC, Emami MR. Asteroid redirection mission evaluation using multiple landers. The Journal of the Astronautical Sciences. 2018 Jun;65:183-204. https://doi.org/10.1007/s40295-017-0125-5

[19] DAMIT, Ďurech J and Sidorin V. Astronomical Institute of the Charles University. https://astro.troja.mff.cuni.cz/projects/damit/asteroid_models/view/3083, 2019. 2022.08.21.

[20] Yang H, Gong S, Baoyin H. Two-impulse transfer orbits connecting equilibrium points of irregular-shaped asteroids. Astrophysics and Space Science. 2015 May;357:1-1. https://doi.org/10.1007/s10509-015-2262-2

HOW TO CITE THIS ARTICLE:

Fahimeh Barzamini , Jafar Roshanian , Mahdi Jafari Nadoushan ,“ *Optimal Path Planning of a Spacecraft via a Deep Neural Network for Soft Landing on the Irregular-Shaped 433 Eros Asteroid*”, Journal of Aerospace Science and Technology, Vol 17, No1,2024, pp, 81-89

DOI:https://doi.org/10.22034/jast.2023.423239.1168
URL: https://jast.ias.ir/article_184788.html