UDC 629.5

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DETERMINATION OF THE FORCE EXERTED BY AN ION BEAM ON A SPACE DEBRIS OBJECT FROM THE EDGES OF ITS IMAGES USING DEEP LEARNING

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The goal of this article is to develop an effective image preprocessing algorithm and a neural network model for determining the force to be transmitted to a space debris object (SDO) for its non-contact deorbit.

In the development and study of the algorithm, use was made of methods of theoretical mechanics, machine learning, computer vision, and computer simulation. The force is determined using a photo taken by an onboard camera. To increase the efficiency of the neural network, an algorithm was developed for feature recognition by the SDO edge in the photo. The algorithm, on the one hand, selects a sufficient number of features to describe the properties of the figure and, on the other hand, significantly reduces the amount of data at the neural network input. A dataset with the features and corresponding reference force values was created for model training. A neural network model was developed to determine the force to be exerted on a SDO from the SDO features. The model was tested using a set of eighteen calculated cases to determine the effectiveness, accuracy, and speed of the algorithm. The proposed algorithm was compared with two existing ones: the method of central projections onto an auxiliary plane and the multilayered neural network model that calculates the force using the SDO orientation parameters. The comparison was performed using the root mean square error, the maximum absolute error, and the maximum relative error. The test results are presented as tables and graphs.

The proposed approach makes it possible to develop a system of SDO non-contact removal that does not need to determine the exact relative position and orientation with respect to the active spacecraft. Instead, the algorithm uses camera-taken photos, from which the features necessary for calculation are extracted. This makes it possible to reduce the requirements for its computing elements, to abandon sensors for determining the relative position and orientation, and to reduce the cost of the system.

Keywords: *deep leaning, artificial intelligence, computer vision, space debris removal.*

1. Bombardelli C., Pelaez J. Ion beam shepherd for contactless space debris removal. Journal of Guid-ance, Control, and Dynamics. 2011. V. 34. No. 3. Pp. 916-920.
https://doi.org/10.2514/1.51832

2. Merino M., Cichocki F., Ahedo E. A collisionless plasma thruster plume expansion model. Plasma Sources Science and Technology. 2015. V. 24. No. 3. 035006.
https://doi.org/10.1088/0963-0252/24/3/035006

3. Bombardelli C., Urrutxua H., Merino M., Ahedo E., Pelaez J. Relative dynamics and control of an ion beam shepherd satellite. Spaceflight Mechanics. 2012. V. 143. Pp. 2145 -2158.

4. Alpatov A., Cichocki F., Fokov A., Khoroshylov S., Merino M., Zakrzhevskii A. Algorithm for deter-mination of force transmitted by plume of ion thruster to orbital object using photo camera. 66th Interna-tional Astronautical Congress, Jerusalem, Israel. 2015. Pp. 1-9.

5. Fokov, A. A., Khoroshilov, S. V. Validation of simplified method for calculation of transmitted force from plume of electric thruster to orbital object. Aviatsionno-Kosmicheskaya Tekhnika i Tekhnologiya. 2016. No. 2. Pp. 55-66.

6. M. Redka, S. Khoroshylov. Determination of the force impact of an ion thruster plume on an orbital object via deep learning. Space Sci. & Technol. 2022. No. 28. Pp. 15-26.
https://doi.org/10.15407/knit2022.05.015

7. Dudani S. A., Breeding K. J., McGhee R. B. Aircraft identification by moment invariants. IEEE Trans-actions on Computers. 1977. V. C-26. No. 1. Pp. 39-46.
https://doi.org/10.1109/TC.1977.5009272

8. Flusser J., Suk T. A moment-based approach to registration of images with affine geometric distor-tion. IEEE Transactions on Geoscience and Remote Sensing. 1994. V. 32. No. 2. Pp. 382-387.
https://doi.org/10.1109/36.295052

9. Canny J. A computational approach to edge detection. IEEE Transactions on Pattern Analysis and Machine Intelligence. 1986. V. PAMI-8. No. 6. Pp. 679-698.
https://doi.org/10.1109/TPAMI.1986.4767851

10. Xu X., Constantinides A. G. Practical issues concerning moment invariants. Journal of Systems En-gineering and Electronics. 1996. V. 7. No. 1. Pp. 43-57.

11. Ming-Kuei Hu. Visual pattern recognition by moment invariants. IEEE Transactions on Information Theory. 1962. V. 8. No. 2. Pp. 179-187.
https://doi.org/10.1109/TIT.1962.1057692

12. Mitchell T. Machine Learning. McGraw-Hill Education (ISE Editions), 1997. 352 pp.

13. Cybenko G. Approximation by superpositions of a sigmoidal function. Mathematics of Control, Sig-nals, and Systems. 1992. V. 5. No. 4. P. 455.
https://doi.org/10.1007/BF02134016

14. Hornik K. Approximation capabilities of multilayer feedforward networks. Neural Networks. 1991. V. 4. No. 2. Pp. 251-257.
https://doi.org/10.1016/0893-6080(91)90009-T

15. Glorot X., Y. Bengio Y. Understanding the difficulty of training deep feedforward neural networks. Proc. of the Thirteenth International Conference on Artificial Intelligence and Statistics. Proc. of Machine Learning Research. 2010. No. 9. Pp. 249-256.

Received on May 2, 2023,
in final form on June 4, 2023