Deep neural networks for analysis of Mercury's planetary exosphere

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Abstract. The emergence of Artificial Intelligence's Deep Neural Networks (DNNs) as a method for analysis of spatial and temporal data gives us a new avenue for research of the processes inherent to planetary exospheres and their interaction with the planetary environment. Hereby, it will be presented a particular study on how in-situ observations of the elemental composition of Mercury's exosphere may serve as an indication of the surface regolith mineral composition below, through predictions given by pre-trained DNNs. In this case the main driver, considered to generate the exosphere, is the micrometeoroid impact vaporization (MIV), which is seen as the dominant process in the night-side hemisphere of the planet. The training datasets will be constructed from randomly generated virtual surfaces, which will aim to generalize the training of the AI models to various types and compositions of the regolith. Different Neural Network models, which include fully-connected networks and Convolutional Neural Networks, will be compared both in giving supervised classification through multivariate regression predictions, and in reconstructing the regolith mineralogy maps. Furthermore, ways to expand the Deep Neural Networks to pattern recognition and knowledge discovery will be explored beyond the surface-exosphere interaction, as well as the possibilities for transfer learning and online learning with the acquisition of real planetary data. The development of such data analysis algorithms will be shown especially in view of the upcoming arrival of the ESA/JAXA's BepiColombo mission to Mercury, the innermost planet, in 2025, with its variety of instruments able to capture the dynamics of the tenuous Hermean environment. Ultimately, would be targeted the implementation of such AI algorithms within the Ground Segment pipeline software architecture of the experiment BepiColombo/MPO/SERENA, composed by four ion and neutral particle detectors.

1. Introduction

Planetary exospheres are the expressions of many processes and interactions within a planetary environment. Their atomic and molecular compositions and dynamics may be an indication of how the planet reacts to external factors like the solar wind and the dust environment around it, what is the connection between different processes and the dynamics of matter around the planet, and even about particular features of the planet like its surface composition. Through the use of Artificial Intelligence and its Deep Neural Network algorithms (DNN), we can explore in depth the relationships between the planetary environment's components. In particular, this study will show how DNN's can be utilized within the data analysis of Mercury's exosphere to predict (reconstruct) the surface mineralogy underneath. This is achieved by modeling the dominant process for generation of the exosphere on the night side of the planet - the bombardment by micrometeorites, which results in Micrometeorite Impact Vaporization (MIV) of the components of the surface regolith. The MIV model is used to derive the composition of the exosphere at different altitudes, so that it could be observed by an orbiting spacecraft equipped with neutral particle detectors and routed to the DNN's for predictions and analysis. The detection of the neutral particles in Mercury's exosphere will be shown in view of the upcoming BepiColombo ESA/JAXA mission, which with its two spacecraft - the Mercury Planetary Orbiter (MPO) and the Mercury Magnetospheric Orbiter (MMO) - presents a unique opportunity to study the planet from two different vantage points with a variety of instruments and sensors. The development of the Deep Neural Networks and the subsequent scientific analysis are envisioned as a part of the Ground Segment of the suite of neutral and charged particle detectors SERENA (Search for Exospheric Refilling and Emitted Natural Abundances) on-board the MPO.

2. The Model - Exosphere Generation by MIV

In this work the generation of the exosphere is limited to the contribution from Micrometeorite Impact Vaporization (MIV) as a suspected dominant process on the night side of the planet. The diameter of the area on the surface, over which the exosphere collects the vapor particles is roughly equal to the altitude where these particles are observed [1] (see Fig. 1), while also the higher altitudes are less densely populated due to a Maxwellian distribution of the energy of the excited particles [2]. The model considers the contribution of the dust disk around Mercury's orbit constant, the micrometeoroid input flux uniform, and the release of elements from the surface 100% efficient. The magnitude of the input flux, the velocity of the impactor, and the chemistry of the impact are not taken into account. Thus, the resulting exosphere is one with a normalized density, and a blurring proportional to the altitude. These rough approximations are noted for the future expansions of the model beyond the prototype DNN's application shown below (see Sec. 7).

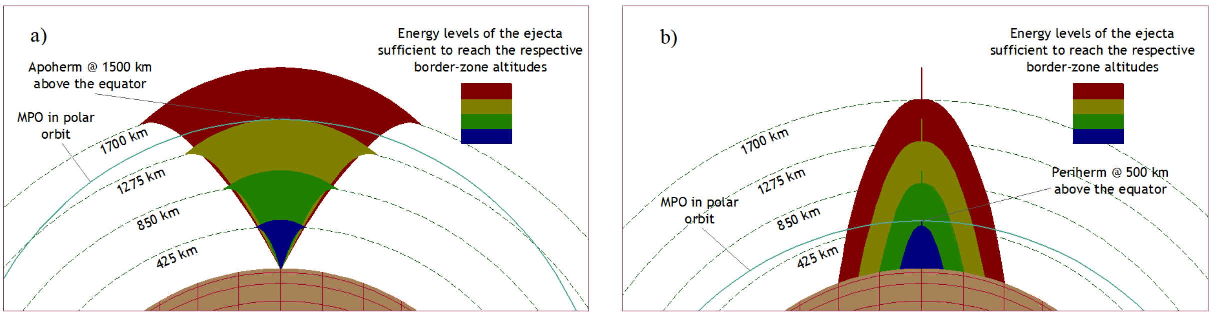

Figure 1. Exospheric particle collection from the surface of the planet: (a) Spread of the vapor from a MIV event on the surface of Mercury showing particles of different energies reaching different altitudes. (b) Contribution of areas on the surface of Mercury to the composition of the exosphere at different altitudes

A simulated model of the Hermean environment is hereby used to generate the regolith and populate the exosphere, which is then followed by a simulated run of the MPO with the SERENA/STROFIO (STart from a ROtating FIeld mass spectrOmeter) through that exosphere and the detection of its neutral composition along its path. The detected particles are the input for the subsequent DNN algorithms. The procedure starts by creating a random regolith composition of the surface - the randomness is needed in order not to overfit the DNNs towards learning a particular composition, which will reduce their ability to generalize their supervised learning and make predictions on unseen (real) examples. Each randomly generated regolith consists of seven minerals in different percentages - Anorthite (CaAl/2Si/2O/8), Albite (NaAlSi/3O/8), Orthoclase (KAlSi/3O/8), Enstatite (Mg/2Si/2O/6), Diopside (MgCaSi/2O/6), Ferrosilite (Fe/2Si/2O/6), Hedenbergite (FeCaSi/2O/6), as those are regarded as the most probable abundant minerals on Mercury [3]. The surface is coarsely divided in 18×36 tiles (latitude by longitude) in a Mercator projection, while the exosphere above is divided also to 18×36×5 sectors at altitudes of 425, 850, 1275 and 1700 km (roughly representing the collection areas underneath) (Fig. 2). Following the random regolith generation is the resolution of its atomic composition at surface level - this splits the minerals into their elemental constituents by mol % - total of eight elements - Na, Ca, Al, Si, O, Mg, Fe and K [4].

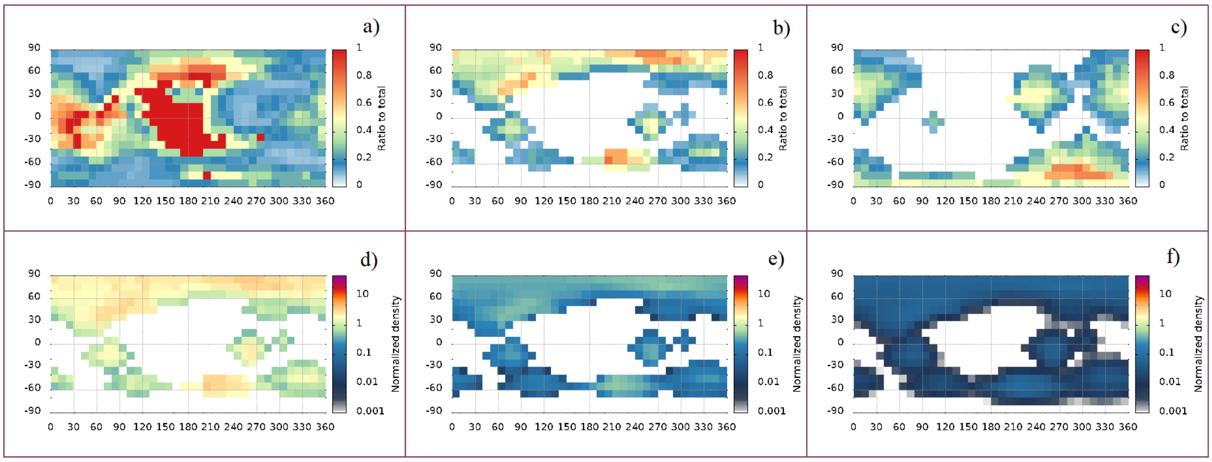

Figure 2. Top panels: Randomly generated simulated surface mineral maps - (a) Anorthite, (b) Orthoclase, (c) Hedenbergite. Bottom panels: The resulting potassium (K) exosphere from the underlying surface through the uniform MIV process from a constant dust disk - (d) at surface level, (e) at an altitude of 425 km, (f) at an altitude of 850 km.

The vapor cloud is then spread above its surface generation area as shown in Fig. 1 to create a non-dynamic exospheric composition of the eight elemental species at different altitudes. When the exosphere is finally generated, the simulated spacecraft with its particle collecting instruments is taking an accelerated swipe through the night exosphere, which results in passes over each area of the simulated surface, but at different altitudes and always at night (see Fig. 5) to collect the data for the following analysis.

3. Instruments for Exospheric Detection

BepiColombo is equipped with a complete suite of instruments to investigate the rocky planet Mercury at its arrival in late 2025. The neutral mass spectrometer STROFIO, included in the SERENA suite is the only detector on-board MPO that will be able to detect and measure the gas cloud of the exosphere of low energies, and resolve its neutral composition through in-situ observations (Fig. 3). In the current examination it is simulated the orbiting spacecraft and the generation of measurements data by STROFIO, which is then processed and fed to the Deep Neural Networks for AI analysis.

4. The Deep Neural Networks

The objective of the Deep Neural Networks in the current analysis is to make a prediction of the surface regolith mineral composition by looking at the densities of the neutral particles

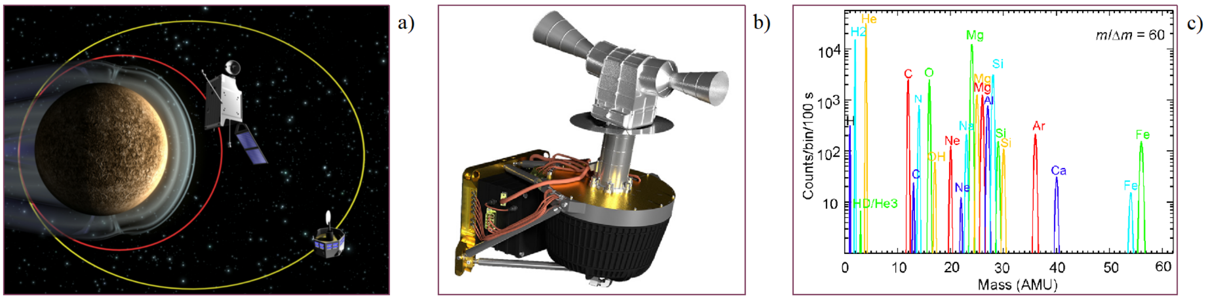

Figure 3. (a) The two orbiters of BepiColombo - MPO on the red orbit, and MMO on the yellow orbit. (b) Flight model of the mass spectrometer SERENA/STROFIO on-board MPO. (c) Expected mass resolution of the neutral exosphere by STROFIO (detection counts vs. molecular mass) [5].

measured by the spectrometer in the exosphere above the planet. There are three types of Deep Neural Networks trained to perform this, all of them supervised learning algorithms: (1) Fully connected multivariate regression, (2) Fully connected multivariate regression on a 3×3 grid, (3) Convolutional Neural Network on a 5×5 grid (Fig. 4).

The inputs to the networks are the readings from the simulated run of STROFIO through the exosphere - a total of 8 elemental densities plus the altitude over the surface. For the 3×3 MVR and the 5×5 CNN variants, the inputs over the surface area in view are also complemented by the readings from the sectors adjacent to the one of interest. The DNNs are created in the Keras programming framework for Python and are iteratively trained, with the same training dataset collected from a batch of 40 different randomly generated regoliths and their corresponding exospheres, to learn by themselves how the inputs non-linearly relate to each other, in order to give as an output the correct predictions about the underlying regolith's mineral composition. After the training phase, the different models are tested and compared by their performance on a previously unseen, simulated environment, which is another randomly generated regolith and exosphere - the test dataset.

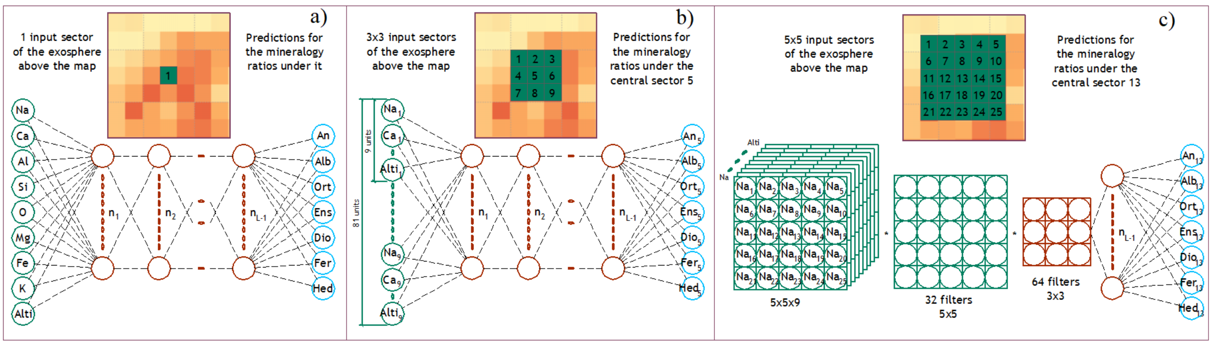

Figure 4. DNN algorithms schematics and input over the map of the surface: (a) (1) MVR, (b) (2) MVR 3×3, (c) (3) CNN 5×5

5. DNN Algorithms Performance

All 3 DNN algorithms show satisfying results in predicting the test dataset. Parts of the map where the spacecraft (S/C) has passed at higher altitudes are more prone to mis-prediction (Fig. 5). In the following Tab. 1 are shown the metrics for comparison. Note that in this case the similarity metrics is based on the Euclidean distance between prediction and true mineral composition of the simulated regolith. It should be noted that the algorithms have more room for optimization, which may include the addition of more features as input, expanding the number of hidden layers, hyperparameter tuning, expanding the training datasets with more examples and training for more iterations [6].

Table 1. Performance of the DNN algorithms in training and on the simulated test dataset

Model	Training Similarity	Training Time	Test Similarity	Test Similarity with Altitude in range 500 km - 1,500 km
Fully Connected MVR	87.94%	786 s	85.95%	89.11% - 81.03%
Fully Connected MVR 3×3 rebinned	87.65%	598 s	84.79%	89.86% - 75.17%
CNN 5×5	83.97%	1,353 s	79.53%	83.57% - 67.88%

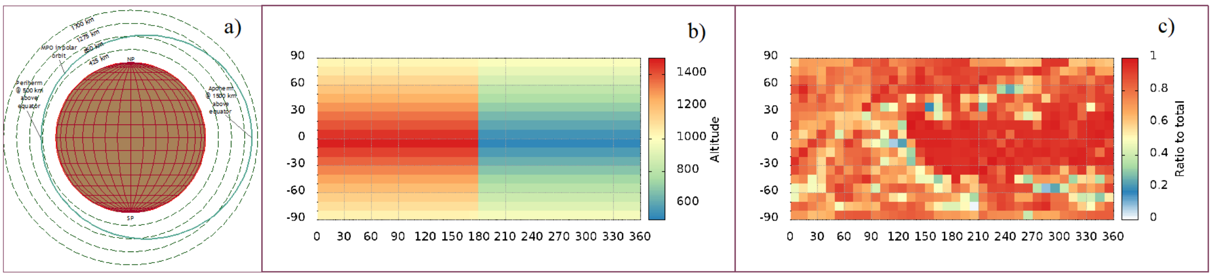

Figure 5. (a) MPO's polar orbit around Mercury (500×1500 km). (b) Mean altitude of the spacecraft's passes above the surface in the simulated run through the test exosphere. (c) Similarity map between True and Predicted mineral composition of the surface (for all minerals)

6. Reconstruction of the Surface Composition

Predictions from the DNN algorithms are hereby used to reconstruct the underlying mineralogy of the surface regolith and compare them with the true simulated mineralogy of the previously unseen by the DNN's examples from the test dataset (test simulated environment). As shown before, the maps have good accuracy in the regions, above which the S/C passes with a low altitude (-60° to +60° Lat, 180° to 360° Long), while high altitude passes (-60° to +60° Lat, 0° to 180° Long) show less accurate predictions for the regolith mineral ratios (see Fig. 6).

7. Future Utilization, Optimization and Improvements

The ultimate aim of this work would be to incorporate the DNN algorithms into the Data Analysis module of the SERENA experiment's Ground Segment, where it would aid the scientific mission in its pursuit of new and better knowledge about Mercury and its exosphere. To achieve this goal, refinements of the presently tested environmental models and algorithms are envisioned, which would allow the DNN's to be trained to distinguish better subtle patterns in the real planetary environment.

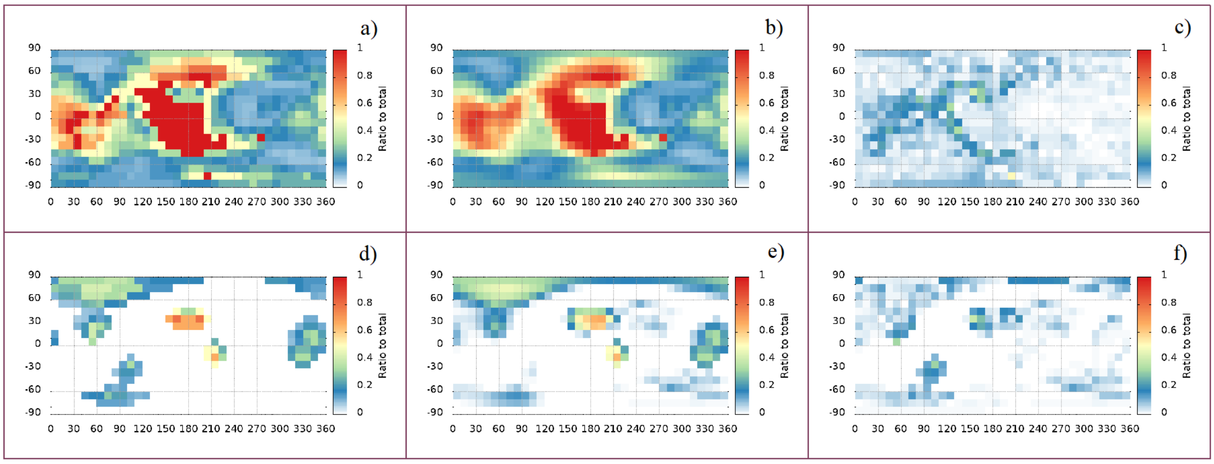

Figure 6. (a) True simulated regolith composition ratio of the Anorthite mineral. (b) Predicted (reconstructed) regolith composition ratio of the Anorthite mineral by the MVR algorithm. (c) Absolute difference between True and Predicted composition ratios for the Anorthite mineral. (d) True simulated regolith composition ratio of the Ferrosilite mineral. (e) Predicted (reconstructed) regolith composition ratio of the Ferrosilite mineral by the MVR algorithm. (f) Absolute difference between True and Predicted composition ratios for the Ferrosilite mineral.

Future improvements on the DNN's will involve optimization of their architecture, and the use of test datasets coming from more precise simulations and/or real data. Their adaptation towards Pattern Recognition and Knowledge Discovery will include the utilization of transfer learning, online learning and a Blackboard system for model proposal by experts. At the same time, the environmental models will be improved by adding more complexity, such as: non-constant dust disk and effects of cometary streams [7], other processes for the generation of the exosphere (ion sputtering, photon stimulated dissociation) during daytime, incomplete activation of different surface elements (activation efficiency) for each process, new molecular species and their interaction, etc.

All of these additions and further sophistication would allow investigating through the Deep Neural Networks not only the surface mineralogy, but also the dynamics of the exosphere itself, as well as expanding the utilization of the algorithms to other planetary bodies.

Acknowledgments
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