Reconstructing Mercury's Southern Hemisphere

Brown Computer Science

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Introduction

This project aims to explore various image reconstruction techniques on the planetary data of Mercury. Planetary data on Mercury's southern hemisphere is low quality due to the near-polar eccentric orbit of the MESSENGER (Mercury Surface, Space Environment, Geochemistry, and Ranging) satellite. This project proposes that by using examples of topographic maps and gravitational fields from other celestial bodies, such as the moon, Mercury's raw data collected by MESSENGER in the southern hemisphere can be reconstructed to a higher quality. By exploring how convolutional neural networks can provide reconstructed models of Mercury's southern hemisphere, researchers can better understand how to apply convolutional neural networks to observe other planetary bodies.

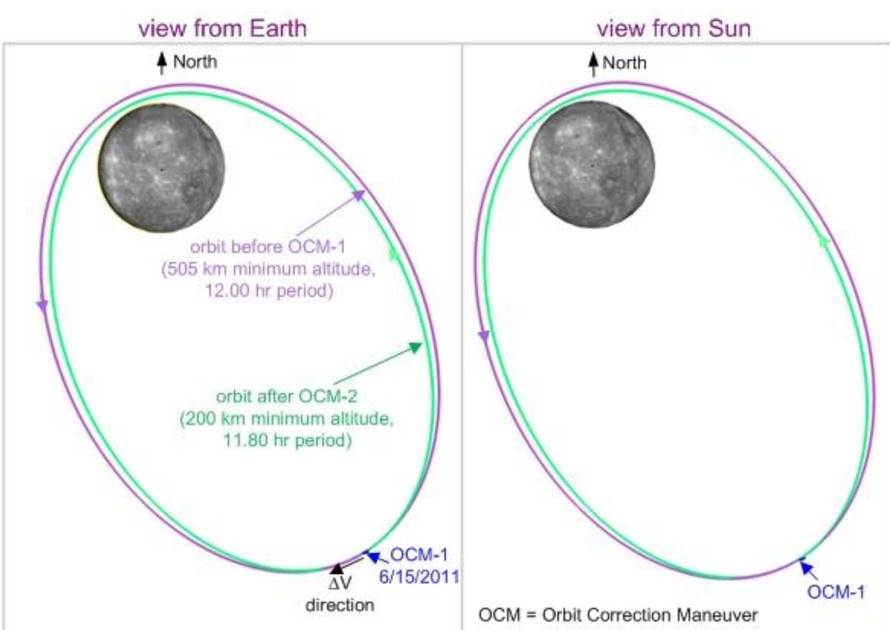

Fig. 1: The MESSENGER satellite's orbit around Mercury

This research extends beyond the scope of planetary science as well. Medical image reconstruction allows clinicians to better diagnose and treat diseases, converting raw data into images that can expose internal structures and shed light on biochemical functions. For Mercury's image reconstruction, it is crucial to incorporate the raw data as well as low degree spherical harmonics to capture both detail and shape. Similarly, across other fields, image reconstruction involves more than simply enhancing visuals, where it also depends on incorporating complex factors that go well beyond basic pixel information.

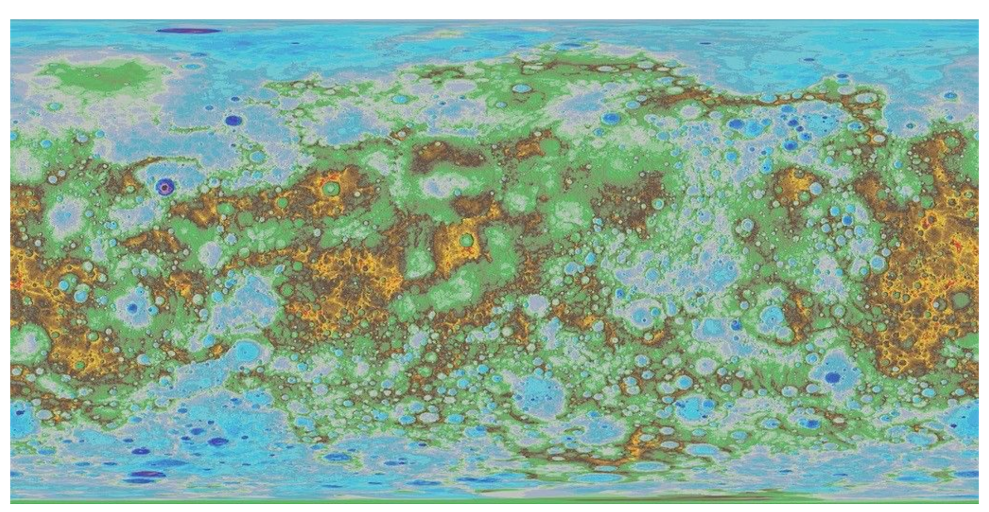

Fig. 2: A colorized hillshade of Mercury's DEM

Methodology

To train our model for reconstructing Mercury's data, we used NASA's dataset from the LRO Mission for the gravitational fields on the moon and the dataset from the MESSENGER for the gravitational fields on Mercury respectively. In addition, we used the digital elevation model (DEM) for both planets to model the topographical features to enhance the reconstructed data.

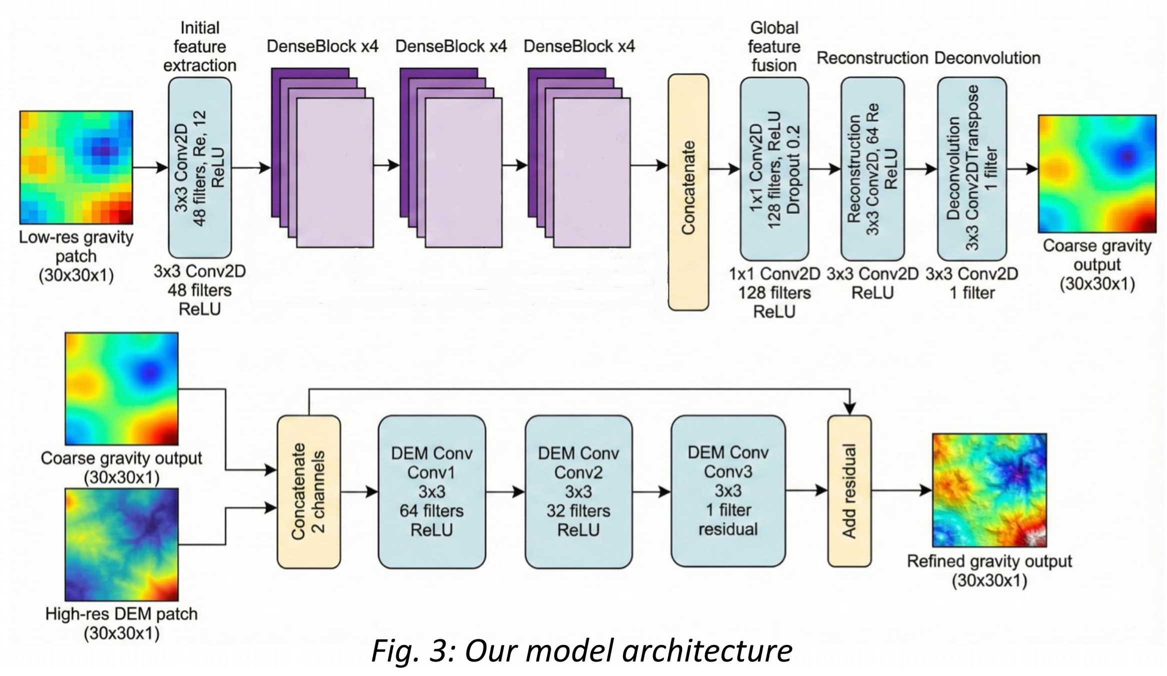

Fig. 3: Our model architecture

For our gravitational data, we use the spherical-harmonic gravity model HgM007 for Mercury, which is then preprocessed to 2D global grids at various degrees (25-100). For Mercury's DEM data, we use the data from MESSENGER downsampled to match the target resolutions. For the lunar training data, we use the lunar GRAIL gravity and LOLA DEM for gravity and DEM respectively for pretraining due to their structural similarity.

For our model, we constructed a replication of the original research paper's architecture using the Tensorflow framework, with minimal changes to adapt to our local computer processing environment. First, the gravitational fields are modelled using a gravity reconstruction network, where the low-degree gravity is mapped to a coarse high-degree gravity using a DenseNet-style CNN. Then the coarse high-degree gravity is concatenated and combined with high-resolution DEM data for spatial structure with a three-layer residual CNN to produce the final gravity data.

We performed pretraining on the lunar gravity and DEM data across multiple degree ranges, then fine-tuned on a small sample of Mercury data to adapt to Mercury's data distribution.

We optimized our model through minimizing mean squared error (MSE) between the network output and target high-degree gravity, and used the Adam optimizer with the default parameters.

Results

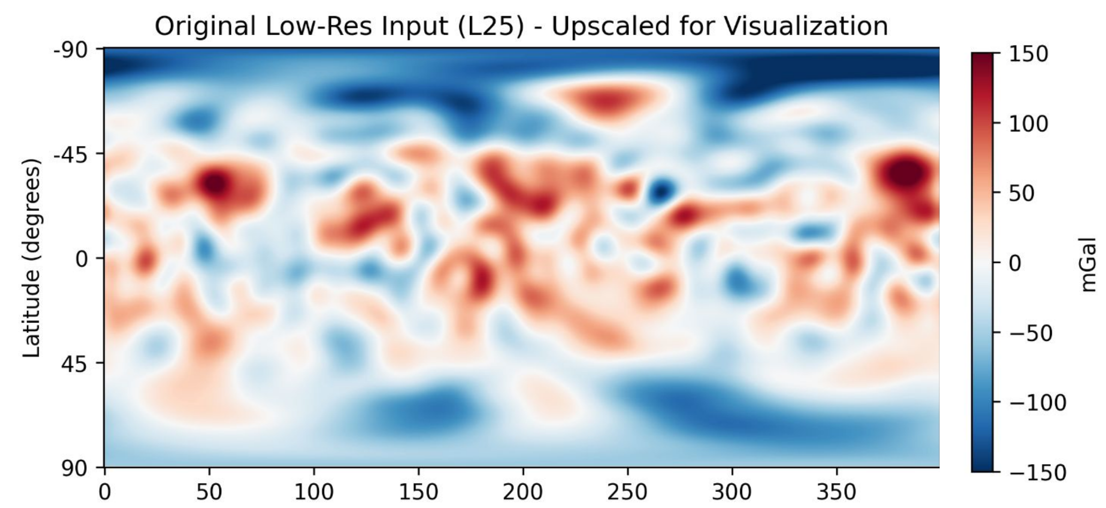

Fig. 4: Original input, up to degree 25

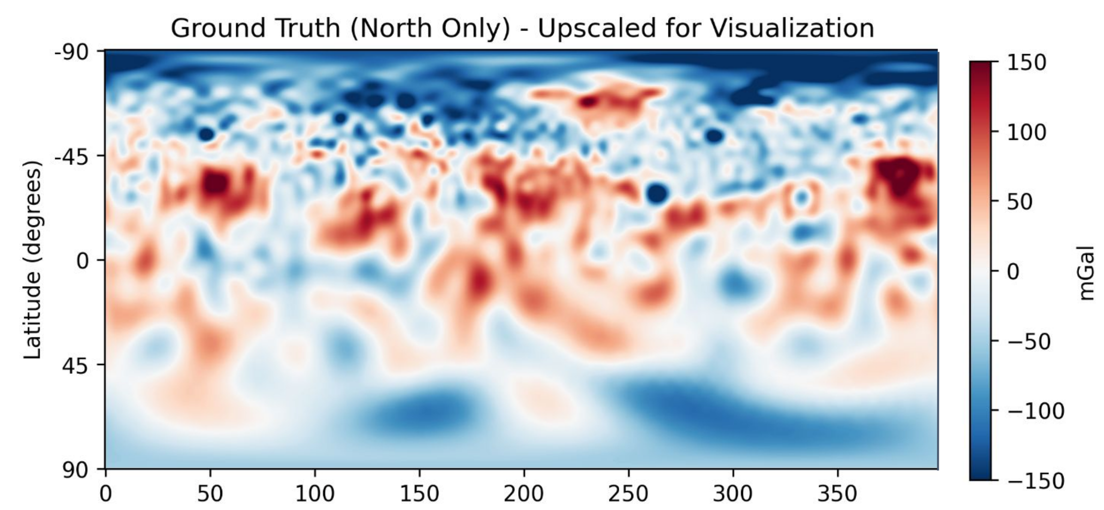

Fig. 5: Original input, up to degree 100

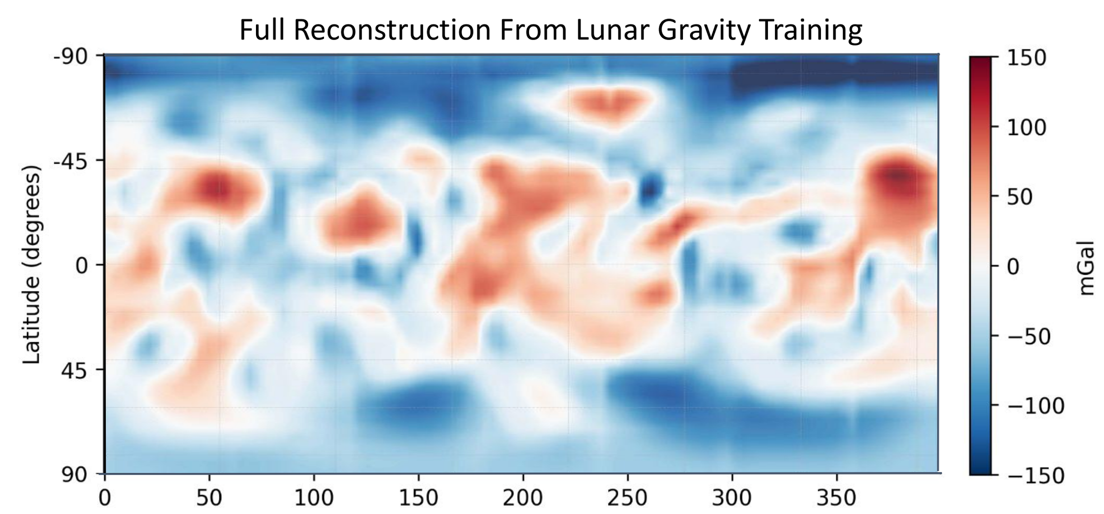

Fig. 6: Full Mercury reconstruction output from training on Lunar gravity data, up to degree 100 with checkerboard effect

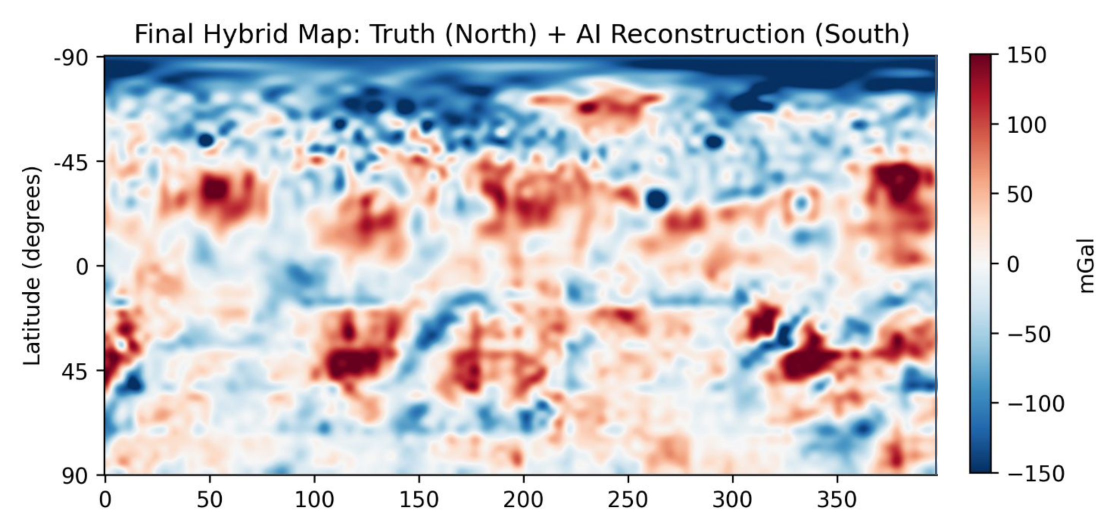

Fig. 7: Northern original input stitched to generated southern output with DEM and Mercury training, up to degree 100

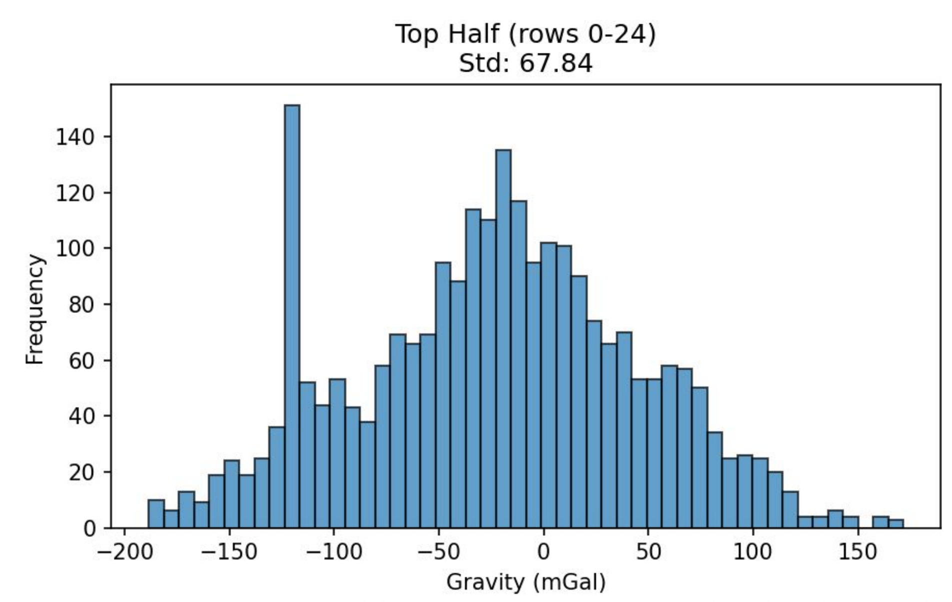

Fig. 8: Histogram of frequency vs. gravity value for the northern half of Mercury

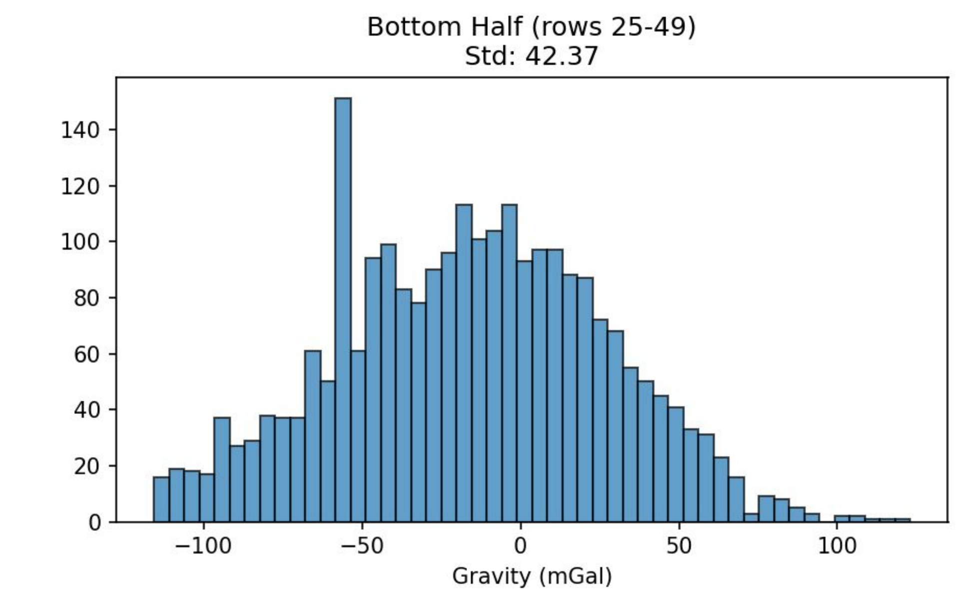

Fig. 9: Histogram of frequency vs. gravity value for the southern half of Mercury

Discussion

Initially, we started by training a model on lunar gravity data and using the traine model to reconstruct Mercury's gravity data. However, as shown by Figure 6, this proved to be unsuccessful, as it was unable to pinpoint finer details in gravity and did not learn to generalize structure when solely trained on lunar data. Training first on lunar gravity and DEM and then training the model on the Mercury's gravity and DEM in northern hemisphere solved both of these issues, allowing for Figure 7 to generate a detailed reconstruction of the southern hemisphere. By stitching the southern generation to the northern hemisphere true data, we have a complete reconstructed gravity map.

In addition, Figure 6 demonstrates the checkerboard effect, where horizontal and vertical grid lines appear. To mitigate this, we reduced the stride size and applied a slight Gaussian blur to smooth sharp transitions. We also observed that gravity distributions differed between the northern and southern hemispheres (Figures 8 and 9), so we used the global distribution to better identify extreme values in the south. Lastly, our initial use of MAE loss likely encouraged the model to output neutral values near 0 mGal. Switching to MSE loss produced a more precise spread between high and low gravitational field values.

One remaining issue is that the reconstruction in Figure 7 produces features that may not be physically meaningful. For instance, it shows average or above-average gravity near the poles, despite the input data providing no such indication. In future work, training the model not only on the Moon but also on additional celestial bodies could improve generalization. Their differing compositions may help the model learn broader gravity patterns instead of overfitting to one or two bodies.

Works Cited: