Guided Inverse Gravity Modeling for Asteroids using Neural Networks

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Introduction

This work is about **inverse gravity modeling**, which means calculating the internal mass distribution of a body from its gravitational field. Studying the mass distribution can give valuable insight about the history of a body and can help build better models of small-bodies. The goal of this work was to adapt a machine learning based inverse gravity modeling method, so that the mass can be predetermined in a certain area. This is useful, because additional information about the mass distribution might be available from other sources. The inversion method should respect the defined mass, while calculating the remaining mass from the gravitational field.

The main results of this work are:

- a **dataset** consisting of mass distributions and corresponding gravitational fields to train **CNN based inversion methods**
- a **customized loss function** for the **GeodesyNet** [2], which enables the specification of mass/density for a certain area

The Dataset

The Dataset is based on 3D models from the 3D Asteroid Catalogue [1]. The mass distributions and gravitational fields are calculated with a **mascon-based method**.

The Loss Function

The original loss function of the GeodesyNets, which is a neural network based inversion method, only measures how well the GeodesyNet adheres to the input gravitational field. To be able to guide the GeodesyNet towards a predefined density in certain regions we added a term to the loss function which measures how closely the GeodesyNet matches the predefined density. This guidance loss is added to the loss based on the gravitational field, and both are weighted with a factor.

Results

The results show that both the GeodesyNet and a comparative mascon based method called masconCUBE are able to match the given guidance density, while still adhering to the input gravitational field, when the new loss function is used. The masconCUBE provides lower errors with respect to the gravitational field in general. Regarding the error on the predefined guidance density, the GeodesyNet performs better on large guidance regions, while the masconCUBE performs better on smaller regions. Both methods are unable to reproduce the guidance density well given only the gravitational field. This means that if a certain density in a certain region is desired, guidance is needed.

References

[1] Greg Frieger. *3D Asteroid Catalogue*. July 3, 2021. URL: `https://3d-asteroids.space/` (visited on 08/17/2024).

[2] Dario Izzo and Pablo Gómez. "Geodesy of irregular small bodies via neural density fields". In: *Communications Engineering* 1.1 (Dec. 2022). ISSN: 2731-3395. DOI: `10.1038/s44172-022-00050-3`. URL: `http://dx.doi.org/10.1038/s44172-022-00050-3`.

GeodesyNets can be successfully **guided** towards specified density areas using a **customized Loss Function.**

A new **Dataset** to train **CNN-based gravity modeling** techniques is introduced.

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$$L_{\kappa MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \kappa \hat{y}_i| \quad (1)$$

Figure 1: The original loss function based on the gravitational field.

$$L_{\kappa G} = \frac{1}{n}\sum_{i=1}^{n} |y_{\delta_G} - \kappa \hat{y}_i| \quad (2)$$

Figure 2: The guidance loss function.

$$L = (1-g)\cdot L_{\kappa MAE} + g \cdot L_{\kappa G} \quad (3)$$

Figure 3: The combined and scaled loss parts forming the complete loss function.

$$\kappa = \frac{\sum_{i=1}^{n} \hat{y}_i y_i}{\sum_{i=1}^{n} y_i^2} \quad (4)$$

Figure 4: The mass normalization factor.

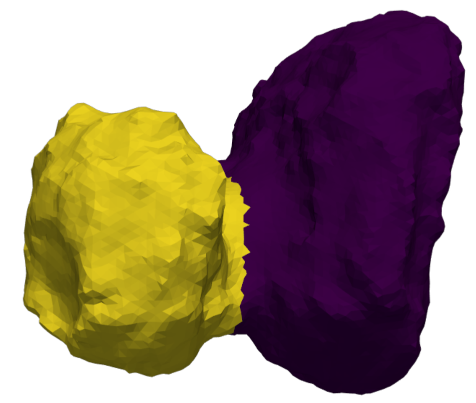

Figure 5: 67P Churyumov-Gerasimenko with a density heterogeneity introduced for its head.

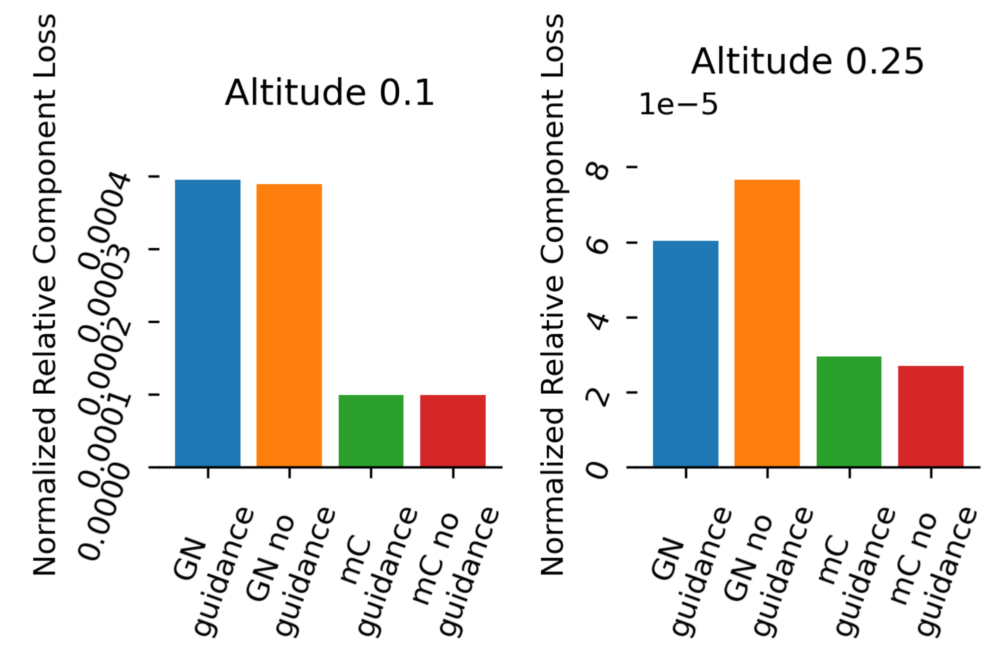

Figure 6: Excerpt from the results for Churyumov-Gerasimenko with three spherical heterogeneities distributed through the body. The spheres have radii of 0.05, 0.035 and 0.05 and densities of 1, 0.5 and 2.5. A guidance factor of 0.0125 was used for the guidance models.

Ground-truth name	GeodesyNet	masconCUBE
CG sphere	4.448e-04	4.341e-05
CG multi-zero	2.320e-05	0.000e+00
CG multi	1.751e-04	7.840e-05
CG plane	7.732e-03	1.203e-02
Bennu sphere	1.251e-04	1.146e-04
Bennu multi	1.229e-04	2.864e-05
Bennu plane	7.470e-03	2.490e-02

Figure 7: Final guidance losses for the studied ground-truths, for GeodesyNets and masconCUBEs.

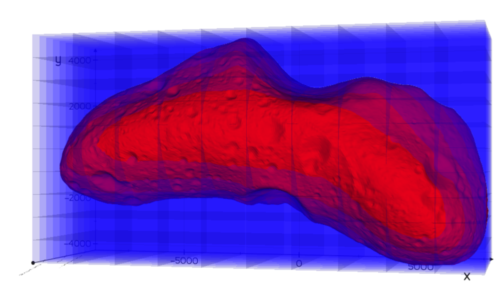

Figure 8: Filling the bounding box with mascons. Here ten subdivisions were used, leading to 1000 mascons.

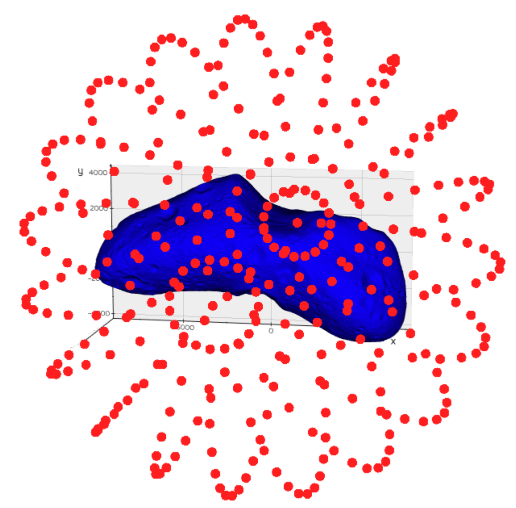

Figure 9: The sampled points creating a sampling sphere around the asteroid.

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