



Machine learning tools to develop 3D shape models of near-Earth asteroids from radar observations

Agata Rożek (1), Michael W. Busch (2) Sean E. Marshall (3), Grace C. Young (4), Adam D. Cobb (4), Chedy Raïssi (5), Yarin Gal (4), Lance A. M. Benner (6), Patrick A. Taylor (7) and Stephen C. Lowry (1) (1) School of Physical Sciences, University of Kent, Canterbury, UK (a.rożek@kent.ac.uk), (2) SETI Institute, Mountain View, USA, (3) Arecibo Observatory, University of Central Florida, Puerto Rico, USA, (4) Computer Science Department, University of Oxford, Oxford, UK, (5) INRIA, Villers-les-Nancy, France, (6) Planetary Science Section, Jet Propulsion Laboratory / Caltech, Pasadena, CA, USA, (7) Lunar and Planetary Institute, Universities Space Research Association, Texas, USA.

Abstract

The specific shapes of near-Earth asteroids (NEAs) depend on their internal structure and dynamical history. Physical models of NEAs are required to understand the dynamical processes in the Solar System, to successfully plan spacecraft missions, and set up impact mitigation strategies. The best ground-based source of shape information is the planetary radar. Reconstructing asteroid shapes and spins from radar data is a computationally intensive task. Shape modelling also requires extensive human oversight to ensure that computational methods find physically feasible results, so detailed shape models are available for a small sample of radar-observed asteroids. Here, we discuss the deep-learning neural network approach to increase efficiency of the shape modelling task that was prototyped during the NASA Frontier Development Lab (FDL). We present the outcome of the FDL, and the strategy for full development of the neural-networks based asteroid shape modelling tools.

The near-Earth asteroids (NEAs) are a population of objects on orbits that cross or come near that of Earth; primarily rocky “rubble-pile” aggregates made up of fragments of rock and ice held together by self-gravity and cohesion. The morphology of NEAs’ shapes is linked to their compositions, internal structures, and dynamical histories, giving us insight into the processes that form them. Detailed shape models are valuable for modelling of shape-sensitive non-gravitational forces, i.e. YORP and Yarkovsky, which play a significant part in their dynamical evolution and bringing asteroids into the vicinity of the Earth. Knowledge of NEAs’ shapes can also help facilitate future asteroid exploration and planetary defence mission planning.

Delay-Doppler radar observations are a unique source of Earth-based information about the physical properties of NEAs [1]. However, producing asteroid shapes from radar data is a computationally intensive task. Unlike in optical images, multiple points on an asteroid’s surface (having the same distance to the observer and relative velocity) map to the same position in a delay-Doppler radar image. The SHAPE software, currently used by the radar community [2] requires extensive human oversight through gradual improvements in the fitted 3D shape model. Therefore, the process of constructing a 3D shape and spin-state model for a single asteroid can take several months.

Our study team has identified major bottlenecks in the shape determination of NEAs and developed machine learning methods to overcome them [3]. With a sufficiently extensive training set, radar images of real and synthetic asteroids with known shapes, and properly adjusted parameters for learning, a neural network can be trained to recognise features in radar images and link them to surface features on the asteroid. Once the network has been sufficiently trained, it will produce an approximate 3D shape almost instantaneously.

When completed; these tools will allow much more extensive exploration of the physical properties of radar-detected asteroids, rapidly analysing existing and new radar datasets. We will present the current state of the project and discuss the work required to complete it.

This work was initially supported by the NASA Frontier Development Lab (FDL) programme.

References

- [1] L.A.M. Benner et al. Asteroids IV, 165. 2015.
- [2] C. Magri et al. Icarus, 186:152, 2007.
- [3] C. Raïssi et al. DPS proc., 326.11, 2016