A Search for Smooth Terrains on Asteroid (101955) Bennu using Machine Learning

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Abstract

On the surface of asteroids, smooth terrains are typically associated with the presence of fine regolith material which may be sampled by spacecraft missions. Here we use machine learning to perform an automatic search for smooth areas on the surface of asteroid (101955) Bennu using images from NASA’s OSIRIS-REx mission. We train, validate and test a random forest classifier on images containing smooth areas previously detected and labeled by field experts. Despite the variety of textures on the surface of Bennu, the algorithm reaches 90% in accuracy at testing. When deployed on new images, the classifier confirms the findings of manual search campaigns and highlights that field experts may experience fatigue when searching for regions of interest over the surface of planetary bodies.

1. Introduction

OSIRIS-REx is a NASA New Frontiers mission that will return at least 60 g of pristine surface material from near-Earth asteroid (101955) Bennu [2]. The sample collection maneuver may be successfully performed only in areas designated as safe (i.e., navigation can fly to it) and where ingestible regolith (particles < 2 cm) is present. If such criteria are satisfied, then the scientific value of one site over another will guide site selection. In March 2019, the OSIRIS-REx Camera Suite (OCAMS) [3] performed a survey of the surface at low phase angle from an equatorial station, at a resolution of about 5 cm/pixel. The images were used by the team to look for smooth areas which may indicate the presence of fine regolith material. A first search led to the identification of ~36 sites of interest. A follow-up manual search campaign carried out by over 20 members of the science team found 158 additional candidates, 75% of which were located in the northern hemisphere.

In general, human vision is excellent at recognizing areas of interest in an image. However, recent advancement in computer vision proved that machines are able to match—and in some cases improve upon—human performances and to correct for human fatigue occurring during repetitive tasks (e.g., [1]). Motivated by this, we experimented with an automatic search for smooth areas on the surface of the asteroid Bennu using machine learning (ML). The goal is to complement the human effort in searching for candidate sampling sites and to confirm that ML is a valuable and reliable support tool for sample site selection.

2. Methodology

We use supervised ML to streamline pre-processed training images with known textures into a model that can later classify textures in new images. The term “texture” here refers to discriminative, statistical patterns of pixels in the sample image, with the underlying assumption that these features capture information of geological interest such as the presence of unconsolidated material and rocks. The classifier is a customized version of the “Texturecam” software, a pixel-classification random forest developed at NASA’s Jet Propulsion Laboratory for automatic classification and mapping of geologic features [4, and references therein].

Our training dataset is composed of 36 1024x1024 pixel images of previously identified smooth and rough sites (e.g., Fig. 1A). The images were labeled by field experts according to three classes: smooth terrain, rough terrain, and unknown (Fig. 1B). We train and validate the classifier on 26 of these images (~70% of the whole dataset), and we use the other 30% of the data (10 images, e.g., Fig. 1C) for testing, i.e., assessment of the performance of the classifier when deployed on unseen data.
3. Results

The application of the ML algorithm on the 10 testing images gives an accuracy equal to 90 ± 7% (computed pixel by pixel). As a comparison, a blind selection of smooth regions within the image (“random search”) has an accuracy lower than 40%. We also find that the classifier gets confused where boulder texture resembles that of smooth terrains (e.g., blue ellipse, Fig 1C). To minimize the occurrence of false positives, we mask the known boulders in the images, then we deploy the algorithm to look for smooth regions on additional PolyCam images. The classifier detects areas on the surface that strongly correlate with those found by human operators during the manual campaign effort. Moreover, the classifier also finds at least three new smooth areas in the southern hemisphere that were skipped in the previous search by human operators.

The smooth areas detected by the ML algorithm appear to be equally distributed on the surface of the asteroid (56.56% in the northern hemisphere vs 43.44% in the southern hemisphere). This result is in contrast with the statistics of the manual search campaigns, whose findings are mostly concentrated in the northern hemisphere. Given the excellent correlation between the sites found by human operators and those by the ML algorithm, we conclude that the north-south asymmetry is likely due to human fatigue: the field experts started the survey from the north pole and, progressively moving towards the south, they got tired and thus less efficient in recognizing smooth areas.

4. Conclusion

The smooth terrain map generated by the classifier contributes to a group of regions of interest established for continued study and consideration for sampling. This computer-vision exercise confirms the value of ML in supporting space missions. Furthermore, given the reduced computational runtime, the method can also be employed directly on-board future missions to increase their autonomy in decision-making. Future research on the topic includes the application of the algorithm to other bodies, such as asteroid Ryugu and comet 67P/CG, and the assessment of relative performances.

References


