Automated detection of impact craters on Mars using Bayesian models

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Introduction

The goal of this study is to explore an information theoretic approach to automated landform detection in planetary remote sensing data. This approach utilizes Bayesian Inference to propose and test a range of hypotheses regarding the content of an image to infer the likelihood of a landform being located within a scene and to estimate its geometric properties.

As an initial test case, we have applied a Bayesian Inference framework to the identification of impact craters on Mars with diameters ranging from 250 m to 500 m. Such craters are well resolved within Mars Reconnaissance Orbiter (MRO) High Resolution Imaging Science Experiment (HiRISE) data. HiRISE stereo-pairs and derived Digital Terrain Models (DTMs) allow us to verify inferred three-dimensional geometries.

In our Bayesian modeling approach to representing the properties of impact craters, hypotheses are parameterized models of crater structure (centroid location, depth, radius, outer rim height, etc.) along with environmental context that affects the crater’s appearance (location of the sun as it affects shadows and other lighting conditions, geological properties of the region in which the crater is located, etc.). Prior knowledge comes in the form of soft constraints each of these parameters, such as how large craters tend to be, how their size and shape is affected by the terrain geology in which they were formed, etc. Note that all of these prior soft constraints are informed by prior knowledge and theory about Mars geology, processes involved in crater formation, etc. Evidence is then in the form of properties of the image taken of a crater, such as pixel intensities and supporting image metadata. Our likelihood function for our model then assigns a value indicating how well such pixel intensities and supporting image metadata agree with a specific model. Combining our prior belief in the probability of those model parameters with the likelihood score gives us our posterior probability of the model given the evidence, per Bayes’ Rule.

Using this method we are able to both search for impact craters within satellite images of planetary surfaces and reconstruct the three-dimensional shape of the observed craters.

Discussion

Our Bayesian modeling approach can both detect the occurrence of landforms (e.g., impact craters) in HiRISE imagery and employ image metadata, such as subsolar azimuth, phase angle, and emission angle, to estimate crater morphology. This method may therefore be used to locate impact craters and infer their depth to diameter ratio using only a single image. However, continued work is required to improve probabilistic models of crater shape and account for variations in crater morphologies that deviate from parabolic geometries. For instance, in Arcadia Planitia, impacts into permafrost can generate terraced crater morphologies (Fig. 1), which cannot be reasonably modeled using a parabolic fit. As such, we will generate a series of potential models of crater morphologies and employ information about the target region to help inform the prior probability distributions of these models (Fig. 2). We are also working toward using improved textural information and scattering models, based on dust cover indices, to refine the synthetically illuminated topographic models used to compare the hypothesized crater morphologies with spacecraft observations (Fig. 3). Additionally, we will extend the crater models to a larger range of sizes and develop new models that may be used to identify secondary impact craters and distinguish them from primary craters. Together these approaches provide an effective approach to crater detection on planetary surfaces.

Bayesian Inference

Science is driven by the development of testable hypotheses (a single instance of which is a theory) that provide explanations for and predictions of observations (or evidence, E). Within a probabilistic approach, the basis for comparing different model hypotheses amounts to seeking the hypothesis with the highest probability given the observed evidence: P (H | E). Unfortunately, it is usually not easy to compute this quantity directly. Within a Bayesian modeling framework, this conditional probability of the hypothesis given the evidence is decomposed by Bayes’ Rule (Eq. 1).

These probabilities represent two general sources of information, which can be combined in Bayes Rule: (1) contributions of the evidence itself for selecting amongst models; and (2) incorporation of background or prior knowledge about which models are more probable. The role of evidence and its direct relation to the model comes from the likelihood, the probability of the evidence given a particular model, P(E | H). As the parameters of the model are changed, the evidence becomes more or less likely, and this forms the basis for searching for models that better account for the data.

A relatively high likelihood score indicates that the evidence was likely produced by the particular hypothesis, H, while a relatively low likelihood indicates the evidence was not likely generated from that hypothesis, and therefore the evidence does not support that hypothesis. However, selecting the “best fit” model based solely on the likelihood runs the risk of “over fitting” to the particular evidence, E, which may include noise and other forms of bias in how we came to observe that data. It also ignores prior, often invaluable, knowledge about how we think the world might work, based on accumulated knowledge and background theory. We incorporate this background knowledge as a set of constraints, summarized in the prior probability of any particular model, P(H). P(H) itself is often decomposed into individual contributions of prior knowledge and soft constraints over parameters of the model.

Conclusions

Bayesian inference provides a powerful new approach to landform identification and morphological characterization. The work presented here provides a first step towards this goal, but requires additional development to expand the range of crater models and utilize a wider range of contextual information to inform prior probability distributions of expected surface properties and crater types. Similar approaches may also be extended to other landforms to enable more sophisticated automated mapping of planetary surfaces.

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Figure 1. Terraced crater in Arcadia Planitia, Mars.

Figure 2. Crater morphologies on Mars depend on their geological context, including the nature of the target material and the geological age of the surface. Using geospatial information included within the image metadata and external databases, such geological maps and dust cover indices, we can refine the prior probability distributions of expected crater geometries based on these auxiliary sources of information.

Figure 3. To improve our models of expected crater appearance based on illumination conditions and spacecraft viewing geometry, we are experimenting with new approaches to estimating light scattering properties of the surface based on terrain age, roughness, and dust cover. The solar illumination angle within this synthetically illuminated scene is shown by the yellow arrow.