

# A Two-Stage Classification Approach for Effective Geomorphic Mapping of Planetary Surfaces

Tomasz F. Stepinski<sup>1</sup>, Chaitanya Bagaria<sup>2</sup>

<sup>1</sup>Lunar and Planetary Institute, Houston, TX 77058, USA  
Telephone: (+1-281-486-2170)  
Fax: (+1-281-4862162)  
Email: tom@lpi.usra.edu

<sup>2</sup>Dept. of Computer Science, University of Houston, 4800 Calhoun Rd., Houston, TX 77204  
Email: chaitanya.bagaria@gmail.com

## 1. Introduction

Advances in remote sensing from spacecrafts have produced a large amount of data on topography of planetary surfaces. In particular, the entire surface of planet Mars is covered by a digital elevation model (DEM) with a resolution of ~500 m derived from laser altimeter measurements. In addition, an increasing number of sites on Mars are covered by higher resolution DEMs derived from stereo images. The high resolution global DEMs of planet Mercury and the Moon will be available in the near future. Last but not least, most landmasses on Earth are covered by the 30-90 m/pixel DEM produced from data collected by the Shuttle Radar Topography Mission (SRTM). The major tools for understanding the origin and evolution of planetary surfaces are geomorphic and geologic maps that are traditionally created manually on the basis of photo-geologic interpretation. The slowness and expense of manual methods severely limits the area that can be mapped at the level of detail corresponding to the resolution of available elevation data. For example, 1:500,000 geomorphic maps of Mars exist only for a tiny percentage of its surface. Thus, there is a critical need to develop an effective method for automating the process of geomorphic mapping. In this paper we describe a framework for auto-generation of such maps. The resultant maps have information esthetics similar to manually drawn maps and they can be stored in a standard GIS shapefile format. We assert that our method has a combination of features that makes it likely to become a useful exploratory tool for planetary scientists.

## 2. Mapping Framework

In the context of this paper a geomorphic map is defined as a thematic map of terrain types or regions, patches of topography having similar terrain attributes. A challenge is to design an efficient algorithm that generates maps which are perceived as useful by the community of end users. Most previously developed mapping methods are pixel-based (for example: Irvin et al. 1997, Hengl and Rossiter 2003, Ehsani and Quiel 2008); an algorithm assigns a terrain type label for each pixel in a DEM separately. Our experience shows that pixel-based maps are not readily accepted by the planetary community which is used to the maps in the vector data format (for example, ESRI shapefile format). Some previously developed mapping methods are segment-based (for example: Dragut and Blaschke 2006, Stepinski et al. 2006); an algorithm assigns terrain type labels for multi-pixel but attribute-homogeneous segments of the landscape. The appearance and format of the resultant maps are acceptable for

planetary analysts but segment classification is usually achieved via supervised learning – a technique ill suited for purpose of data exploration.

Our new unsupervised method combines the best aspects of pixel-based and segment-based mapping approaches. The core idea is to design a two-stage classifier consisting of a pixel-based *base* classifier and a segment-based *meta* classifier. A base classifier is applied to multiple pixels in a neighborhood of a focus pixel resulting in an ensemble of terrain type predictions. A meta classifier is an unsupervised segmentation/classification algorithm that combines these predictions and outputs a segment-based map of emergent terrain regions or classes. Hereafter we will refer to labels derived by a base classifier as “terrain types” and to labels derived by a meta classifier as “terrain classes.”

## 2.1 Base Classifier

Our method constitutes a “framework” inasmuch as it works with any base classifier. From a practical point of view a rule-based classifier is probably the best choice for this stage of the method. The rule-based classifier uses empirical knowledge to construct a decision tree; submitting a set of terrain attributes to a trunk of the tree results in a terrain type label at the leave of the tree. A number of such classifiers (for example, Wood 1996, Gallant et al. 2005, Iwahashi and Pike 2007) have been developed, and all of them could be used as the base classifier in our method. From planetary perspective a classifier proposed by Iwahashi and Pike (2007) is attractive because, using only three terrain attributes (slope, convexity, and texture), it assigns one of possible 16 terrain types to each pixel in a DEM. Because it uses the nested means technique to construct a decision tree, the meanings of the terrain types do not correspond directly to named terrestrial formations, thus, they won't lose their relevance in application to non-terrestrial surfaces.

## 2.2 Meta Classifier

For a neighborhood of a focus pixel we use an  $N \times N$  square window. The value of  $N$  controls the level of generalization from terrain types to terrain classes;  $N=11$  is used in present calculations. The labels of terrain types from this neighbourhood form an ensemble used by the meta classifier to assign a terrain class to the focus pixel. A 19-features vector is calculated from the ensemble. The first 16 features are normalized frequencies of terrain types in the ensemble. The last three features measure pattern of terrain types in a neighborhood and are based on a modification of Multi-Scale Local Binary Pattern (LBP) concept (Ojala et al. 2002). The 19-features vector is used by the meta classifier to generate a final map. We use the Recursive Hierarchical Segmentation (RHSEG) algorithm (Tilton, 2000) that *simultaneously* segments the DEM and cluster the segments into terrain classes. The RHSEG is an iterative algorithm that produces hierarchies of both, segmentation levels, and clustering levels. Stopping the RHSEG at a given iteration level yields a map of a certain geographical and feature-space resolutions.

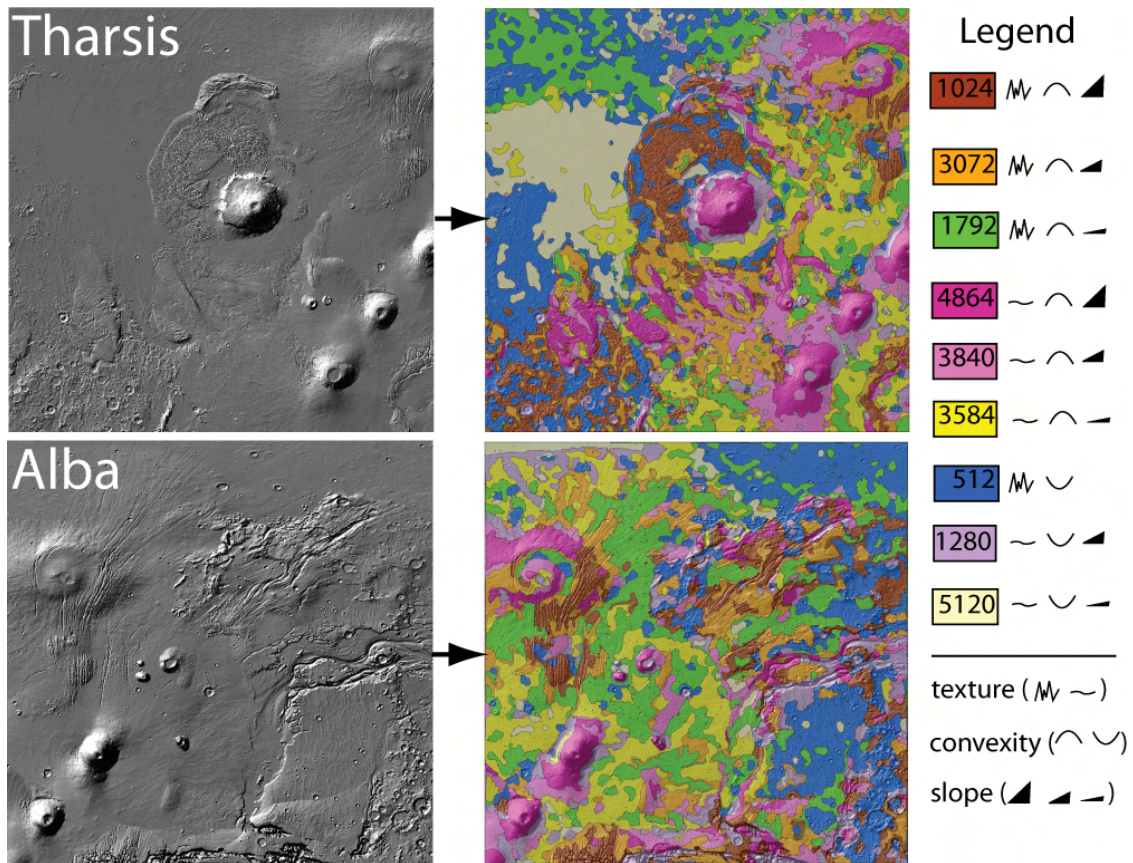


Figure 1. Auto-generated geomorphic maps of Tharsis and Alba regions on Mars.

### 3. Applications

In order to illustrate our method we have applied it to two large, partially overlapping regions on Mars referred to as Tharsis (centered on  $-137^{\circ}\text{E}$  and  $13^{\circ}\text{N}$ ) and Alba (centered on  $-85^{\circ}\text{E}$  and  $25^{\circ}\text{N}$ ), after prominent features in each site. In order to efficiently demonstrate an application of our mapping technique to large sites the global DEM was resampled to 4 km/pixel and the 1024 x 1024 pixels clips were taken to represent the two sites. The base classification was calculated using an AML script, and 19-features vectors were calculated using a Matlab code. Final map was obtained using the RHSEG software. Figure 1 shows the maps of the two sites obtained by stopping the RHSEG at level 11 of the hierarchy when segments are clustered into just 9 generic terrain classes. The classes are post-interpreted (see the legend) on the basis of frequencies of terrain types contributing to the classes.

The map generated by our method have higher visual appeal than pixel-based (or even segment-based) maps of homogenous terrain types because they partition sites in a fashion similar to what an analyst would do manually – into fewer larger, more heterogeneous areas corresponding to terrain classes. Existing, manually drawn geomorphic maps of planetary surfaces concentrate on few selected landforms and cannot facilitate validation of our auto-mapping. Geologic maps provide exhaustive mapping of a site and are formally comparable to our maps, however a geologic map uses many additional criteria besides surface morphology to define units so only a qualitative validation is possible. Figure 2 shows a comparison between the auto-generated and geologic maps of the Tharsis region. There is a rough correspondence between spatial distribution of terrain classes and geologic units. Thus, the immediate

application of our technique is as an *exploratory* tool to offer a quick first draft of geologic map that needs to be further revised and elaborated by an analyst.

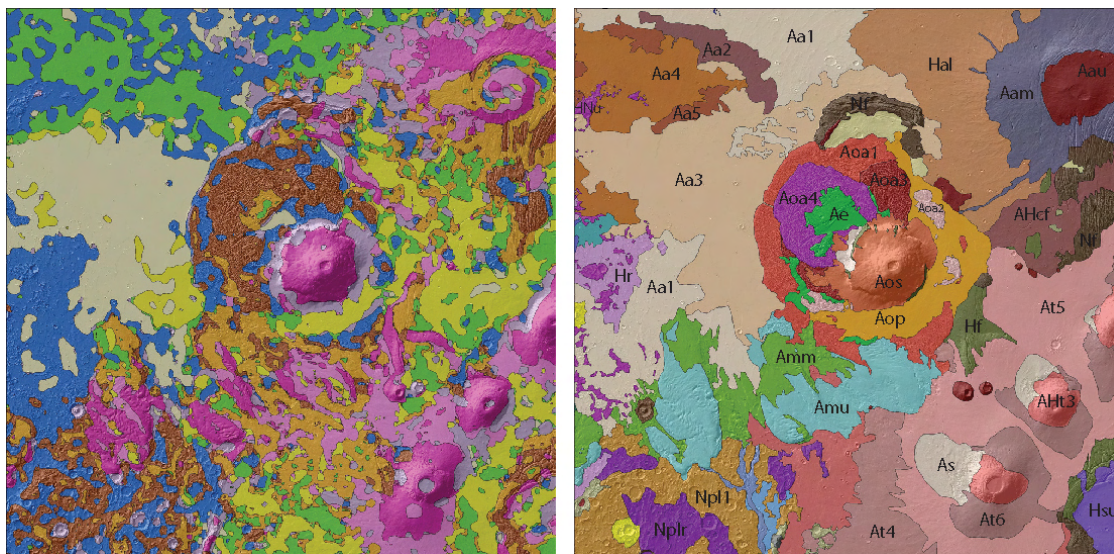


Figure 2. Tharsis region: comparison of auto-generated geomorphic map (left) and manually drawn geologic map (right) with prominent units indicated by labels.

Because we have used a base classifier that assigns terrain types on the basis of statistics of site's terrain, the precise physical meanings of terrain classes change from site to site. For example, there are some small differences in the meaning of classes in the maps of Tharsis and Alba; a full narrative of the classes would reflect these differences. This is why there are small differences in mapping an overlapping part of Tharsis and Alba sites. In order to map a series of sites with classes of exactly the same meaning, a base classifier needs to be used on a concatenation of pixels from all the sites. Moreover, the segments in a selected site should be treated as a training set, and the segments in all other sites should be labeled using a supervised classification technique. However, in most planetary geomorphology applications an analyst focuses on a single site.

#### 4. Discussion

Exhaustive auto-mapping of landscape elements is a challenging problem. Our two-stage classification method yields a map of terrain classes that is an improvement over maps generated by a single-stage classification algorithm. The improved appearance and utility of our map is achieved by a meta classifier that generalizes numerous homogenous terrain types into fewer more heterogeneous terrain classes. This improvement comes at a computational cost; each site shown in this paper required 7 hours of processing time using a 2.0 GHz Intel processor with only a fraction of that time needed for an execution of the base classifier, and the bulk of the time needed for an execution of the meta classifier. The method is robust; we have utilized it, without any modification, to generate a map of the continent of Africa using the SRTM data. For mapping terrestrial sites it may be more advantageous to use a base classifier described by Gallant et al. (2005) which is modeled after a manual method developed by Hammond (1964) – a standard in terrestrial landform mapping. However, an exhaustive auto-mapping of landform types (as opposed to terrain classes) may not be

feasible using our technique because such landforms are recognized by a combination of DEM-derivable terrain attributes and morphogenetic criteria that cannot be derived from the DEM.

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