GEOMORPHOLOGIC FEATURE EXTRACTION AND CLUSTERING OF MARTIAN DTM DATA

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Introduction: Grouping areas with similar characteristics is a tedious and time-consuming task of planetary geomorphology. In this work, we explore the capabilities of automated approaches as a tool to support and to speed up this process. In contrast to current deep learning approaches which largely lack interpretability and may require large amounts of training data [1], our feature-based approach is a lightweight algorithm which enables the interpretation of 'what is going on inside. This is due to the fact that it is based on simple geomorphologic structures. We apply the method to a region on Mars using the MOLA digital terrain model [2,3] and discuss the results.

Methods: Geomorphologic mapping is essentially a clustering task which relies on features, i.e. mathematical representations of geologic structures . In the feature space, nearby points have similar geomorphologic characteristics which can be grouped by employing clustering algorithms. Finally, the results are visualized in a map.

Features: We start with digital terrain models (MOLA DTM [2]) to derive features according to [4]. As an alternative to differential geometry [5] or differential topography [6], in [4] geomorphons are constructed which are based on Local Ternary Patterns (LTP) [7]. Geomorphons mathematically represent ten common geomorphologic structures, namely: peaks, ridges, shoulders, spurs, slopes, hollows, footslopes, valleys, pits and flat areas. However, the results of a Geomorphon are calculated pixel-wise with a low dependence on the surroundings. To incorporate more context information, we calculate the weighted average of the Geomorphon results in a circular neighborhood. The weights are determined by a 2D-Gaussian kernel. Finally, each pixel is associated with a feature vector which consists of ten entries where each entry represents the weighted occurrence of the different geomorphologic structures in its neighborhood.

Clustering: In order to group similar patterns, we employ two clustering algorithms, i.e. k-means++ [8] and Gaussian mixture models [9]. The k-means++ algorithm extends the famous Lloyd algorithm [10] with a better estimation of the initial cluster points. This algorithm divides the data points in the feature space into k regions such that the distance of the points from the cluster centers becomes minimal.

Gaussian mixture models are probability density functions which consist of a weighted sum of parameterized normal distribution component densities. The parameters are determined iteratively by the expectation-maximization algorithm [9].

Results: We applied our method to a region in Utopia Planitia on Mars [40°N, 120°E] which exhibits a variety of different landforms (Figure 1 left). The results of the geomorphon algorithm are shown in Figure 1 (right). Each pixel is associated with a color that represents the one out of ten geomorphons which most closely resembles the local topography. We vary two parameters: The size of the Gaussian kernels which determines how much context information is incorporated and the number of clusters. The results of the k-means++ algorithm are displayed in Figure 2. The rows represent different kernel sizes and the columns stand for different numbers of clusters. In the same way, the results of the GMM algorithm are shown in Figure 3. It can be observed that the segmentation highly depends on the choice of parameters. Two trends can be identified. First, the window-size determines the extent of continuous segments. The larger the window size, the larger the segments. Secondly, the cluster number controls how many different segments are found. Large windows (s=100) and small clusters numbers (n=4) yield very coarse segmentations. Small windows (s=20) and larger cluster numbers (n=8) yield results which give the impression of over-segmentation. The most plausible results from a geomorphologic perspective are generated by the GMM algorithm with (s=60, n=6) (Figure 3, center). It can be observed that all craters and the ejecta are consistently segmented and associated with one class each, the flat regions in the south west are found and the hilly terrain in the north is associated with one cluster. Generally, the results obtained by GMM look more plausible than those of k-means.

Conclusion: The clustering algorithms offer high flexibility to generate many potential segmentations of a given target region. To identify realistic results, we recommend to generate several candidates with varying cluster numbers and window sizes and choose the one which is most plausible from the geologic point of view. Promising results can be achieved which encourage further research on automated geomorphologic mapping.

References: [1] Goodfellow, I. et al. 2016, MIT University Press, Boston, USA. [2] Zuber, M. et al. (1992), JGR Planets, 97, (E5), 7781-7797. [3] Neumann, G. A. et al. (2001), JGR Planets, *168,(*E10), 23753-23768. [4] Jasiewicz, J. and Stepinski, T. (2013), Geomorphology, 182, 147 – 156. [5] X. Li et al. (2010), IEEE 2nd Conf. on Env. Sc. and Inf. App. Technology, Wuhan. [6] Stepinski, T. & Vilalta, R. (2005), IEEE Geosci. And Remoten Sensing Letters, 2,3. [7] Liao, W. (2010), IEEE ICPR Conference, Istanbul. [8] Arthur, D. and Vassilvitskii, S. (2007), Proc. of the Annu. ACM-SIAM Symp. on Discrete Algorithms, 8, 1027-1035. [9] Reynolds, D. (2009) in Li, S.Z., Jain, A. (eds) Encyclopedia of Biometrics. Springer, Boston, MA. [10] Lloyd, S. (1982), IEEE Transactions on Information Theory, 28, 129-137.

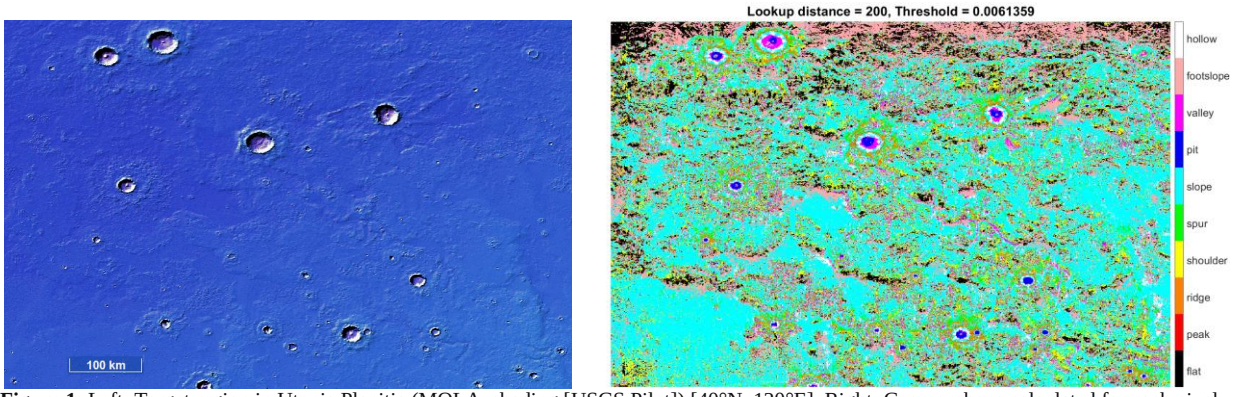

Figure 1: Left: Target region in Utopia Planitia (MOLA shading [USGS Pilot]) [40°N, 120°E], Right: Geomorphons calculated for each pixel.

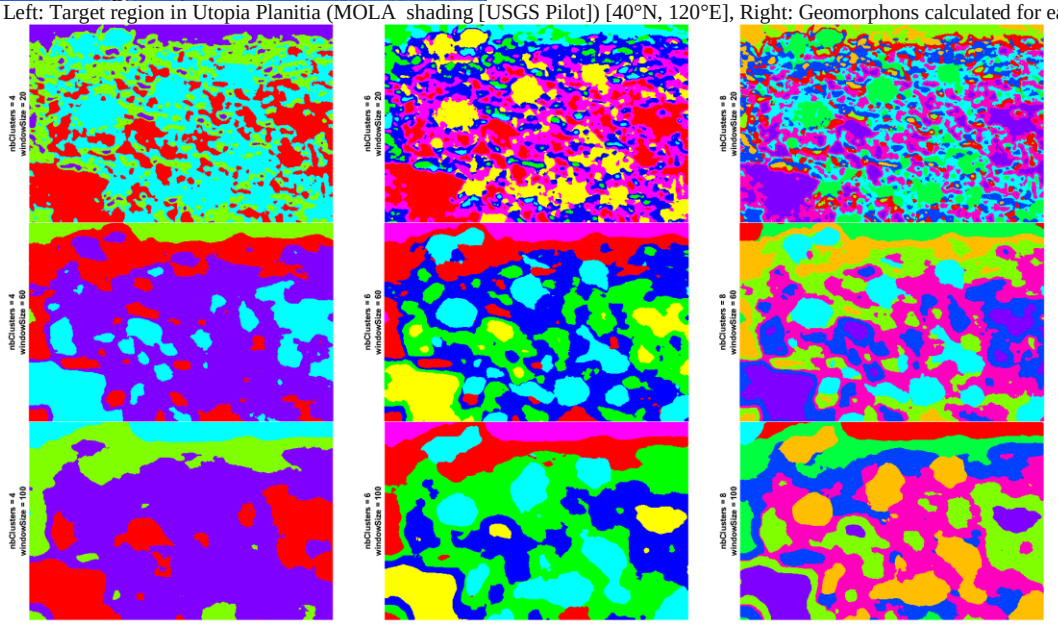

Figure 2: Segmentation obtained by k-means++-algorithm.

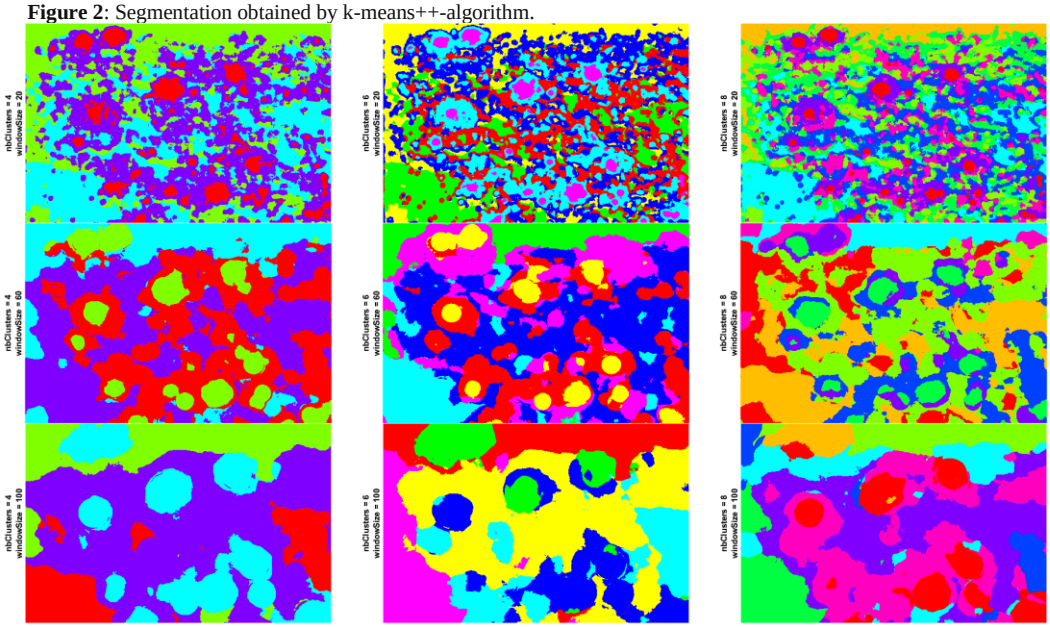

Figure 3: Segmentation obtained by the GMM-algorithm.