AUTOMATED AEOLIAN BEDFORM ORIENTATION MEASUREMENTS IN HIRSE IMAGES – DETERMINING WIND REGIMES ON MARS. E. V. Bohacek[1], A. M. Barrett[2], E. A. Favaro[2], M. R. Balme[2], E. Sefton-Nash[1], R. S. Bahia[1], I. Torres[1]. [1]European Space Agency (ESA), European European Space Research and Technology Centre (ESTEC), Netherlands (eleni.bohacek@esa.int), [2]School of Physical Sciences, The Open University, Walton Hall, Milton Keynes, UK.

Introduction: Apart from the Earth, no planetary body is mapped more extensively and to such fine resolution as Mars. The increasing volume of remote sensing data means we are better equipped than ever to answer the fundamental questions about the history of the planet. However, the volume of data grows much faster than the number of scientists who can use it. Moreover, manual measurement of geological features in Graphical Information Software (GIS) is time-consuming. Machine Learning (ML) is a powerful tool for automating the analysis of ever-increasing volumes of remote sensing data.

Aeolian bedforms exhibit varied morphologies at different scales in remote sensing imagery, therefore, automated detection is a complicated problem. Linear dune fields have been successfully characterized at regional scales using edge detection on Titan from synthetic aperture radar images [1]. Within the field of Earth observation, an edge detection algorithm has been proposed that is optimized for recognizing linear dune fields in panchromatic Landsat 8 data and digital elevation models [2]. Fingerprint minutiae extraction software designed for forensic applications has also successfully detected dune crests and their bifurcations and terminations for linear dunes in the Namib Sand Sea and Strzelecki Desert, and for Transverse Aeolian Ridges (TARs) on Mars [3].

A method for mapping aeolian ripples has been demonstrated using HiRISE imagery from Gale crater [4]. Similarly to earlier studies, this uses a two-step algorithm that segments the bedforms from the surrounding terrain and then detects the crestlines [5]. This study uses the same approach but with a segmentation step that additionally classifies bedforms according to scale and morphology as opposed to foreground-background segmentation.

The aim of this project is to create a more general bedform detection tool that can be applied over larger and more texturally diverse areas of Mars. We do this by applying a new bedform orientation measurement method alongside existing crestline detection methods in the literature. The inevitable difference between automatically measured orientations and human mapped orientations must not be significant enough to suggest a different wind regime. The secondary goal of this project is to demonstrate how ML terrain classifications designed for rover navigation can be effectively repurposed for science.

Method: We measure bedform orientations from HiRISE images using the two-step algorithm:

(1) Segmentation of aeolian bedforms from the surrounding terrain using ML.
(2) Measurement of bedform orientations from crestlines or the bedform area.

The first step applies a machine learning system called the Novelty or Anomaly Hunter – HiRISE (NOAH-H) which was developed to classify terrain in HiRISE images from Oxia Planum and Mawrth Vallis according to texture. It was designed to assess terrain for rover traversability but also demonstrates great potential to be used for science [6]. Each pixel of an input HiRISE image is assigned one of 14 classes. These classes represent every type of terrain that can be found at the Oxia Planum and Mawrth Vallis landing sites. Classes 8 through to 13 are the six types of ripple morphology that are recognized by NOAH-H, summarized in table 1. The morphologies of these 6 bedform classes are different, therefore, they each require different methods to measure their orientation.

8	Large Ripples	Simple form, Continuous
9		Simple form, Isolated
10		Rectilinear form
11	Small Ripples	Continuous
12		Non-continuous, Bedrock substrate
13		Non-continuous, Non-bedrock substrate

Table 1: Subset of ontological classes used by NOAH-H that correspond to aeolian bedforms. Large refers to decimeter scale features and small refers to meter scale features.

The second step of our process measures the bedform orientations for each class of bedforms. For the isolated ripple classes (9, 12, and 13) we developed a pipeline that measures ripple properties using second order central image moments, effectively measuring the orientation of the whole bedform area. The output of this pipeline is a database of bedform coordinates and orientations, which can be readily analyzed in GIS software. For the rectilinear ripples (class 10) we plan to apply the Vaz and Silvestro method [4] to obtain the crestline orientations. The continuous ripple classes (8 and 11) will use the method presented by Telfer et al. [2], Scuderi [3], or Vaz et al. [7] to obtain crestline orientations.

Validation of our method for the isolated ripples is conducted in a region of Oxia Planum, where the aeolian environment has been thoroughly characterized [8]. Class 9, "large simple form isolated ripples", corresponds to the larger-scale TARs in this region, and we compare the orientations derived from human-mapped crestlines to the area orientations measured by our process. The results of this will be presented at LPSC.

Next Steps: Once we implement the methods from the literature for the three remaining continuous bedform classes (8, 10, and 11), we have a powerful tool to measure and analyse bedforms in HiRISE red imagery. The ML step was trained only in Oxia Planum and Mawrth Vallis, yet studies have demonstrated it performs well at detecting aeolian classes at Jezero crater [9]. The tool will be used to characterize the aeolian environment in different reaches of Nirgal Vallis to examine the interaction of aeolian transport with fluvial topography. Preliminary results for this study will be presented at LPSC. We will also build on the validation case study at Oxia Planum by assessing the results from the other 5 bedform classes and ultimately compare these with global climate models (GCMs), which may augment our understanding of aeolian processes in this region. Going forward, we hope to either release the tool as open source or publish a database of TARs (and hopefully other bedforms) for HiRISE coverage in Arabia Terra.

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