USING SELF-ORGANIZING MAPS TO EXPLORE POTENTIAL METHODS FOR AUTOMATICALLY EXTRACTING TRANSVERSE AEOLIAN RIDGES FROM HIRISE IMAGERY.

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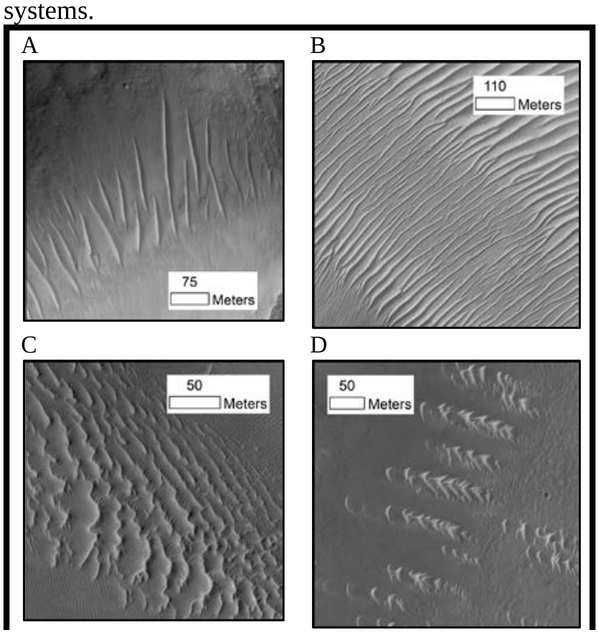
Introduction: Transverse aeolian ridges (TARs) are small-scale relict bedforms on the surface of Mars first detected in narrow-angle images from the Mars Orbiter Camera (MOC) [1], [2]. Dubbed "ridges" to preserve origins as both dunes or ripples, TARs are widespread inactive features on Mars. Their formation, age, composition, and role in the past Martian sediment cycle are poorly understood [2]–[4].

TARs are uniquely well-resolved in High Resolution Imaging Science Experiment (HiRISE) camera images. HiRISE currently provides the highest resolution data of the surface of Mars, with ~0.25 m/pixel resolution in a single panchromatic band [5], which far exceeds other modern imaging systems in orbit around Mars. This high resolution allows for the extraction of geologic and geomorphic information that is simply unavailable from other sensors.

TARs exhibit a range of morphologies (Fig. 1), which are interpreted as likely representing disparate formative or evolutionary processes. Past work has categorized TAR morphologies but relied on manual surveys and classifications [1], [2]. Automating the detection and classification of TARs in HiRISE imagery is an important step towards betting understanding TARs' evolution and role in the Martian aeolian systems.



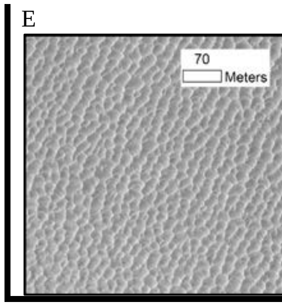


Fig. 1: TAR morphology examples:
A) simple
B) forked
C) sinuous
D) barchan-like
E) networked

This study assesses the feasibility of two approaches to extracting TARs from HiRISE images: 1) a pixel-based approach where each pixel is classified based on how TAR-like it is, or 2) an object-based approach in which TAR pixels are segmented, and then classified in ensemble.

Normally, both of these approaches rely on multi-spectral imagery to discriminate between different classes in a higher dimensional feature-space, but HiRISE imagery is only single-band. Here, six textural transforms are applied to the imagery (Fig. 2) to produce a pseudo-multiband image, which can then be used with typical classification algorithms.

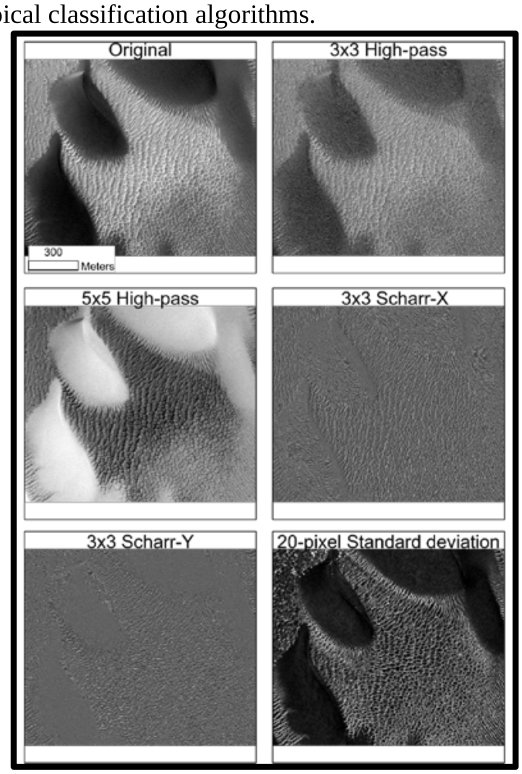


Fig. 2: The six bands that composed each pseudo-multiband image.

Methods: Six 200x200 pixel (100x100 meter) samples of common TAR morphologies (simple, forked, sinuous, and networked) were cropped from three different pseudo-multiband HiRISE images. In total, 24 samples were collected from 12 different HiRISE images. Training samples were manually collected from each sample tile and are used to classify pixels into one of five classes: no TARs (0), simple TARs (1), forked TARs (2), sinuous TARs (3), or networked TARs (4). Each tile was then classified by a random forest (RF) classifier with 50 trees, a depth of 30, and a maximum of 1,000 samples per class to produce a label band for each tile. The multiband samples and the labelled band were converted into 3D numerical arrays, and then into a text file with a column for each band.

The six textural bands of the text file were used to train a self-organizing map (SOM) (also known as a Kohonen map or network) [6], [7]. SOMs are a type of artificial neural network (ANN) that implement unsupervised learning to produce a 2D representation (the map) of the input space of the training samples (Fig. 3). For this project, a 79x79 map was initialized and the neighborhood and learning rate parameters were optimized over 10,000 iterations to minimize the quantization error of the map. The initial SOM weights were then derived from the principle components of the dataset (as recommended in the literature [8]), and the SOM was trained for 100,000 iterations. Using a 75/25% train/test split of the five RF labels, the precision, and recall of the network were tested. The same procedure was repeated with a simple binary classification of TARs/not-TARs.

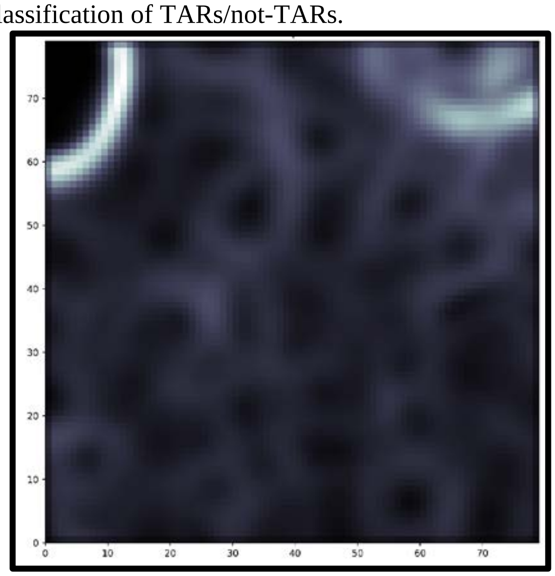


Fig. 3: The distance map of the SOM produced in this project. Light colors indicate large differences between adjacent neurons, dark colors indicate similarity. Non-TAR pixels were mapped to the upper left, while TAR pixels were spread across the rest of the map.

Results: The SOM was only able to classify the TAR morphologies with ~56% precision and ~35% recall. The binary classification was more successful, with 77% precision and 69% recall.

Discussion: The multiband pixel vectors are not useful for distinguishing between TAR morphologies, but could be used to differentiate them from the rest of the Martian landscape. However, the RF-based binary classification of TARs/not TARs was successful in identifying TARs, especially given the diversity of both the TARs and the not-TAR areas in the sample tiles.

Going forward, a more robust and universal RF classifier will be developed. The binary output of this classifier could then be used in combination with a pattern-recognition algorithm to classify TARs based on their disparate shapes (Fig. 4).

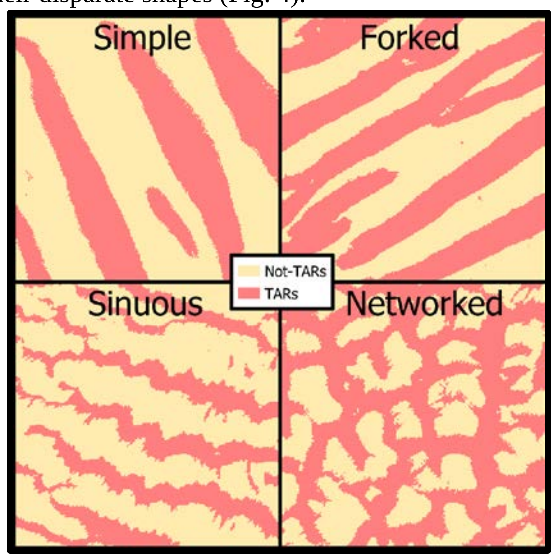


Fig. 4: The shape of each common TAR morphology as generated by binary RF classifiers. Each image is 100x100 meters.

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