AUTOMATED DETECTION OF TRANSVERSE AEOLIAN RIDGES ON MARS USING CONVOLUTIONAL NEURAL NETWORKS AND A FIELD-BASED TERRESTRIAL ORTHOIMAGE TRAINING SET.

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Introduction: Dunes on Mars provide evidence of active and ancient aeolian processes and are critical for understanding the planet's stratigraphy and surface modification history. Active sand transport and ripple migration occurring on Mars has been observed using automated image feature correlation and change detection [1, 2, 3], but genetically-related Transverse Aeolian Ridges (TARs) [e.g., 1] appear to have been stationary over recent history. TARs are commonly imaged by the High Resolution Imaging Science Experiment (HiRISE) camera onboard the Mars Reconnaissance Orbiter (MRO), and our goal is to develop an efficient, automated mapping strategy for TARs to understand their spatial distribution, morphological characteristics, and processes of formation.

Methodology: Mapping TARs and including information such as shape, crest spacing, sinuosity and surface albedo is challenging because of their small footprint in HiRISE images. TARs can be found over large areas, but are typically found in isolated patches. To obtain quantitative topographic information about TAR height and morphology, high-resolution (1 m/pixel) digital terrain models (DTMs) can be constructed from HiRISE stereo-image pairs [5] using ISIS and SOCET SET software. These stereo-photogrammetry methods are based on feature-matching and the algorithms often have difficulty retrieving three-dimensional (3D) information from smooth surfaces, subtle features, or contiguous ripple textures. TARs typically occupy only a small portion of any HiRISE image, which makes processing an entire DTM for these small features a time-consuming task. Likewise, the area and size of TAR bedforms are generally small and near the limit of detection with respect to the spatial resolution (~1 m/pixel) of the DTMs. Although height information is highly desirable for analysis, the pattern of ripple and TAR ridges seen from HiRISE images alone can reveal information about paleo-wind directions, which is important for understanding Martian climate.

Our initial efforts to map TARs focused on manual digitization of TAR patterns and 3D profile extraction, but it became apparent that automated image processing tools would be better for mapping TARs. Various approaches have been taken to automatically map sand ripples in image data by automatic detection of ripple crest patterns [6] and dunes using supervised machine learning [7]. We initially tested techniques [6] and attempted to map TAR patterns using a Canny edge detection scheme [8]. These essentially could detect edges of TAR crests that correspond to the light and dark image contrast produced from light reflected at the planet's surface. These efforts are still in progress, but they initially resulted in both false positive and negative cases of edge detections.

More recently, improved machine learning techniques, termed Convolutional Neural Networks (CNNs) [9], were used to detect, distinguish, and map volcanic rootless cones (VRCs) and impact craters in Elysium Planitia [10]. Despite the similarity in appearance of VRCs and impact craters in HiRISE images, the technique was successful in distinguishing between the two classes and prompted us to implement CNNs to improve mapping and characterization of TAR ripple patterns. Unlike most computer vision techniques, CNNs are particularly effective for pattern recognition within image data because they do not require preprocessing steps to facilitate accurate classifications [10].

Terrestrial analog training. In this work, we extend the CNN technique [10] by building the supervised training set directly from orthoimage data of terrestrial TAR analogs [11, 12] (Fig. 1).

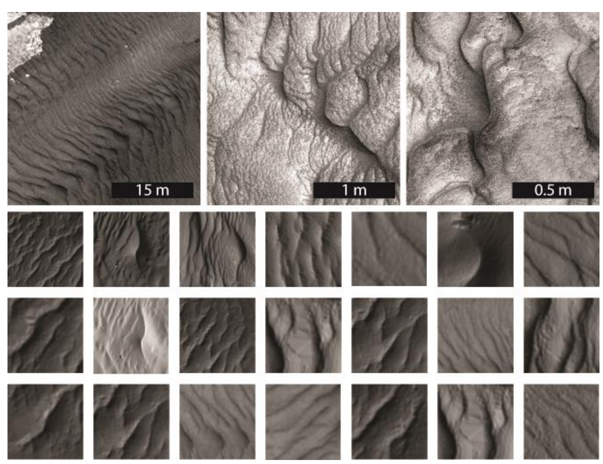

Figure 1. A synthetic orthoimage training set based on 3D models generated from field images of terrestrial TAR analogs in Hawaii, Colorado, and Arizona using multi-view stereo-photogrammetry (MVSP) techniques. The larger top three images show scaled sites, where smaller tiles are dimensional, randomly oriented and are generated both from orthoimages and synthetic DTM models.

Supervised machine learning techniques such as Support Vector Machines (SVMs) [7] and CNNs [9] rely on an image training set that characterizes the features needed for recognition and classification. In planetary remote sensing applications, the training set usually originates from the image source (i.e., the image being classified) and these data lack field-based ground truthing. Fortunately, aeolian bedforms on Earth (e.g., megaripples, granule ripples, and gravel ripples [13–16]), exhibit considerable morphological similarities to those on other planetary surfaces, which implies similarities between their formation mechanisms.

In this study, we employed high-resolution terrestrial orthoimage data (<1 mm/pixel) generated using field-based multi-view stereo-photogrammetry (MVSP) techniques [e.g., 11, 12, 17, 18]. These 3D models have exceptionally high spatial resolution and in the orthoimages (Fig. 1) can be digitally manipulated to have a predefined incidence angle with respect to a synthetic camera. This enables us to use ground-truthed aeolian bedfroms to create a well-characterized terrestrial analog data set with which to train automated landform detection algorithms, such as CNNs.

Results: We show the classification results of training the CNN using a training dataset of 400 points from the original HiRISE image (Figs. 2A and 2B). The results of using the ground-truthed terrestrial training set of 200 synthetic orthoimages under the same conditions (Fig. 2C) is comparable to the CNN application using the martian image training set (Fig. 2B).

Conclusions: CNNs trained using synthetic instrument data, generated from terrestrial analogs, performed comparably to classifications that utilized in-situ HiRISE image training sets. This example demonstrates that well-characterized Earth surface archetypes may be used as training sets for the identififation of aeolian bedforms on other planetary surfaces. The immediate benefit of this work is efficient mapping of TARs and the ability to directly link terrestrial bedforms on Earth to planetary image data. However, CNNs may also be trained using terrestrial analog data to search for a range of other Earth-like surface features without introducing a bias by relying exclusively on in-situ training data drawn from planetary remote sensing observations.

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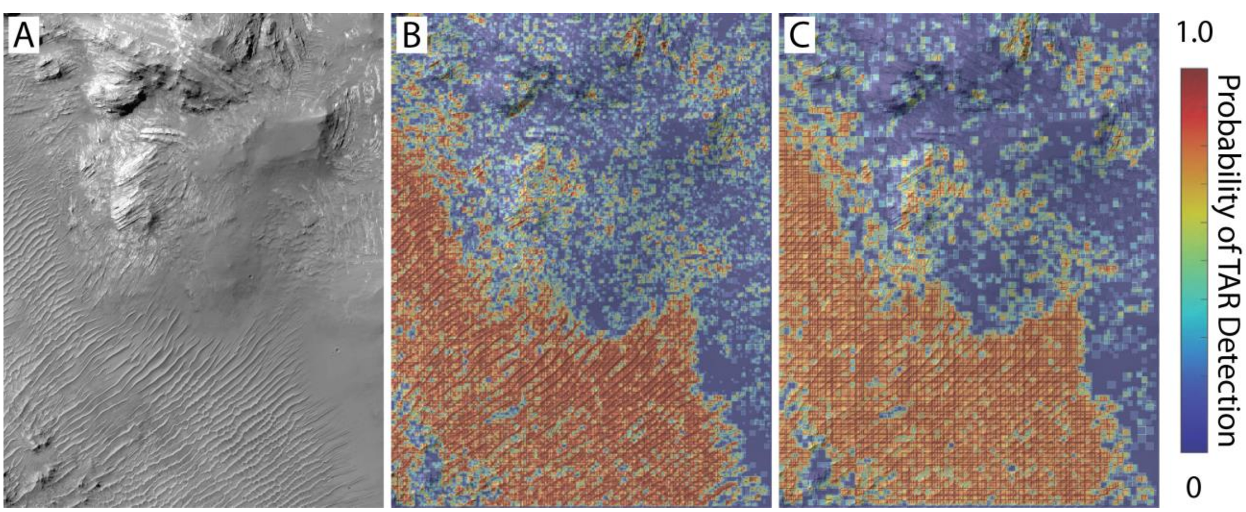

Figure 2. A: Original image (HiRISE ESP_06805_1565) containing TARs emplaced around a layered rock outcrop. B: Results based on the martian HiRISE training set. C: Result using the synthetic terrestrial training set. In B and C the red color of the represent positive TAR detections and blue represent null detections. Map area is 590 × 765 m.