Automated crest-line detection and analysis of sand dune patterns on planetary surfaces.

David Leblanc, Nicholas Lancaster, Mircea Nicholescu, and George Bebis

lblancdavid@gmail.com, nick.lancaster@dri.edu, mircea@cse.unr.edu, bebis@cse.unr.edu

Overview

The goal of this project is to develop an automated crest-line detection method to extract desired features from satellite images of dune fields.

Various Image processing and computer vision techniques will be used used to detect the features and compute morphological properties of a dune-field region.

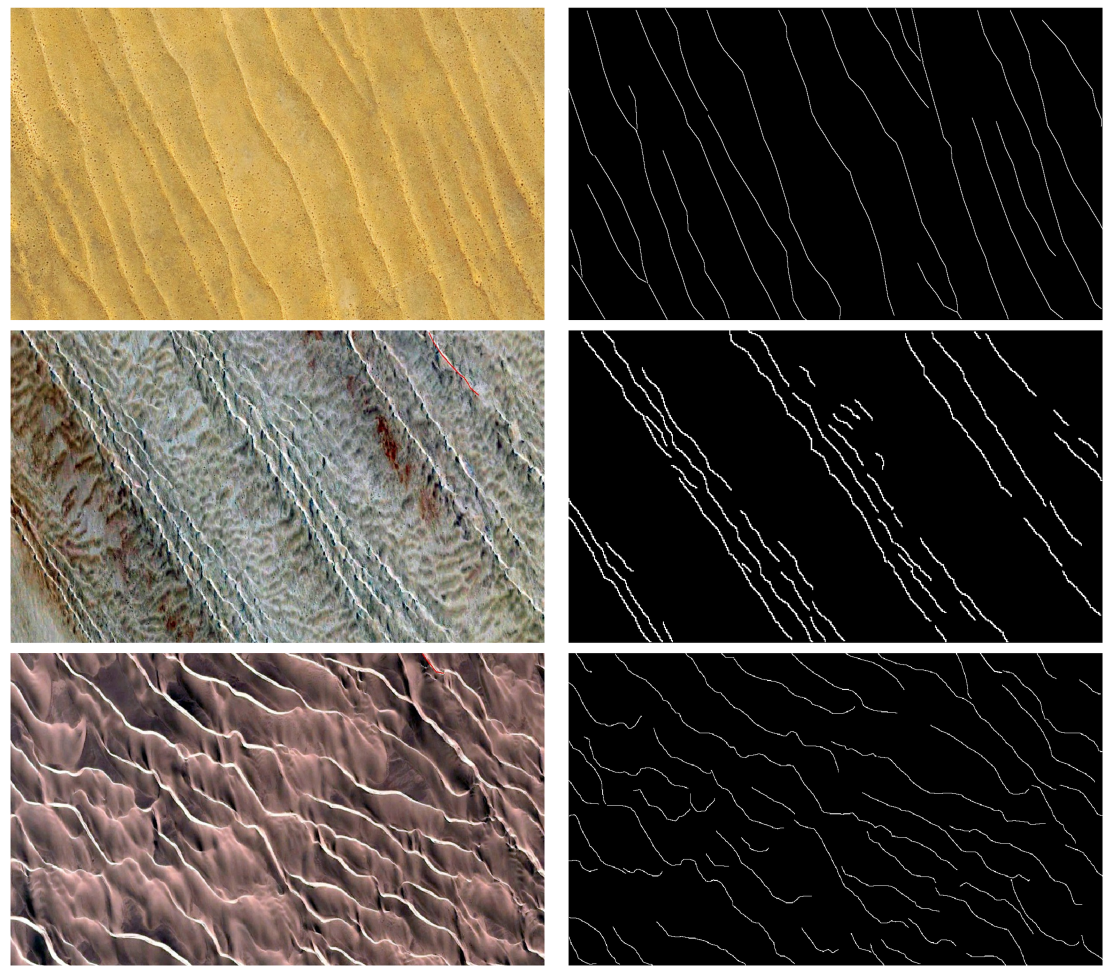
Preliminary work is showing promising results.

Data set

The current data set used consist of a small set of images with crest-line ground truth labeled so accuracy can be determined. Each image includes ground truth which has been manually labeled by an expert.

Images have been retrieved using Google Earth from six distinct regions: Kalahari, Kumtagh, Namib, Simpson, Skeleton Coast, WDC, and White Sands.

These sample images provide a wide range of examples which makes it an adequate for benchmark testing of various methods.



Introduction

Sand dunes are commonly occurring patterns in desert regions on many planets, and range in complexity. Dune-field patterns are believed to behave as self-organizing systems as shown in [1], but what causes the patterns to form is still poorly understood. Extracting meaningful features such as crest length, orientation, spacing, bifurcations, and merging of crests can reveal important information about the specific region's climate and morphological properties. [2]

Our main approach will use gradient information computed from the image. Typically, dune crest-lines have a dominant gradient magnitude and orientation. It many cases, the images have two major dominant gradient orientations, for the sunny and shaded side of the dunes. To determine which dominant orientation represents the desired crest-lines, a histogram of the gradient orientations is used. Peaks in the histogram, after normalization, can help differentiate dune crests from non-dune crests.

Methodology

Currently, we have implemented two main approaches for extracting the crest-lines:

Appearance-based Segmentation: The main goal of this approach is to segment bright regions of the image, which represents the part of the dune illuminated by the sun.

The crest-line can be detected by extracting the contours of segmented regions and choosing the segments in the contour which have the largest and consistent edges.

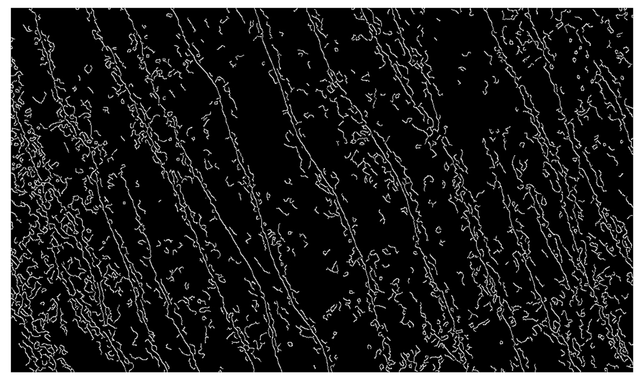
Generally, the segmentation process provides large contiguous regions as shown in **A**, but makes the assumption that crest-lines lie on the edge of a bright region, which is not always correct.

Gradient-based Approach: This approach is centered around edge detection algorithms and gradient computation [3]. We used to popular Canny edge detector (shown in **B**) to detect crest-line candidates.

The Canny edge detector performs generally well at finding the crest-lines, but generates many false positives.

A.

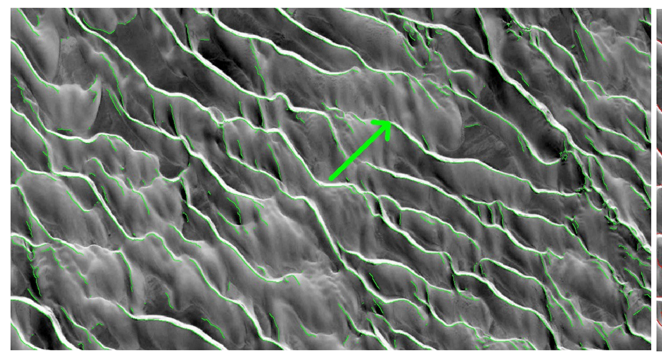
B.



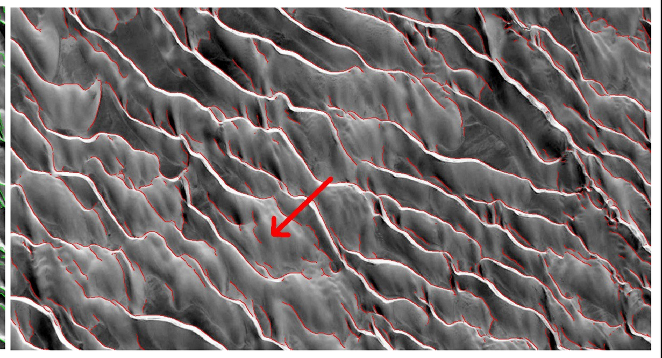
To filter out the false positives, we classify the edges based on their magnitude and direction. By constructing a histogram of the gradient orientations, weighed by the magnitudes, we can determine the dominant orientation by choosing the peak of the histogram.

Typically, two dominant edge orientations are present: One representing the crest-line edges (**C**), and the other is generally the edge of the shadow or valley of the dunes (**D**).

C.



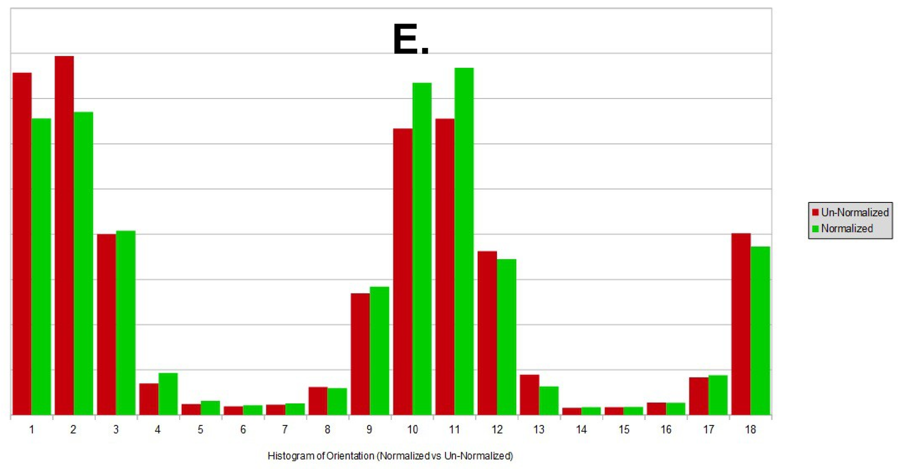
D.



Determining the dominant orientation can be resolved by normalizing the histogram of gradients. The peak in the normalize histogram represents the correct crest-line orientation.

The remaining edges are considered noise and can be filtered out, by size or shape (on-going research).

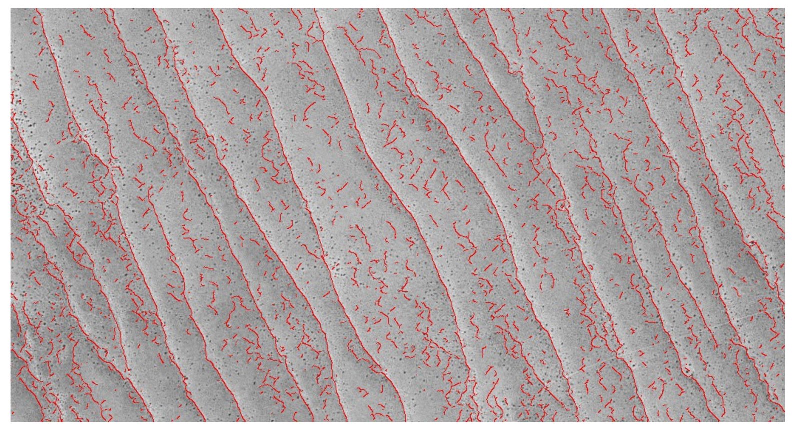
E.



Preliminary Results

The results of the dune crest-line detection (**F**) is compared to the labeled ground truth image.

F.



So far, the crest-line detection algorithm is able to remove most of the false positives which are shadows or valleys of the dunes, but struggles with generally noisy areas.

The accuracy is computed by measuring how much of the ground truth has been detected. A successful detection is determined by a distance e = 5 pixels. If a detected point is at a distance of less the e, then the ground truth point is considered found.

The false positive rate is the percentage of detected points which do not belong to the ground truth. The results for each proposed algorithm are shown in Table 1.

Table 1.

Images	Appearance-Based		Gradient-Based	
	Accuracy	FP	Accuracy	FP
Kalahari	0.9239	**0.5229**	**0.9790**	0.6319
Namib	0.8591	**0.7290**	**0.9738**	0.7730
Simpson	0.4968	**0.6979**	**0.7746**	0.7168
Skeleton Coast	**0.9221**	**0.4461**	0.8602	0.6783
WDC	**0.7005**	**0.5819**	0.6660	0.7235
White Sands	**0.3889**	**0.8257**	0.3719	0.8801

Currently, the accuracy of detection of some of the simpler images is fairly good, but struggles with the more complex dune patterns.

The false positive rate is substantially higher that desired. Further work will focus on improving the filtering of the noise and false detections.

References

[1] Ryan C. Ewing, Gary Kocurek. Aeolian dune field self-organization – implications for the formation of simple versus complex dune-field patterns. *Geomorphology*, 2005

[2] Alex G. Hayes, Ryan C. Ewing, George D. McDonald. Multi-spatial analysis of aeolian dune-field patterns. *Journal of Geomorphology*, 2014

[3] M.W. Telfer, R.M. Fyfe, S. Lewin. Automated mapping of linear dunefield morphometric parameters from remotely-sensed data. *Aeolian Research*, 2015

Conclusion

In conclusion, preliminary work has shown good progress toward achieving automated crest-line detection in dune field patterns. The data set used provided a good testing environment for future improvement of accuracy.

Two methods have been conceived to experiment on the problem. Both provide advantages and disadvantages in different areas, which could mean that a mixture or fusion of the methods could be used to improve overall performance.

The gradient-based method was used to find candidate edges and determine the dominant orientation of the crest-lines. The dominant orientation can be used to filter out non-crest-line candidates such as the shadows and valleys of the dunes.

Overall, the results are promising, but more work is required to improve on the filtering of false positives. Future work will focus mainly on improving the detection of the crest-line, which will lead to improved computation of features of a dune-field.

Acknowledgements

This material is based upon work supported by the National Aeronautics and Space Administration under EPSCoR, George Bebis Grant No. NNX11AM09A issued through the NASA EPSCoR Mission Directorate.