A machine learning approach for automated crest-line detection and analysis of sand dune patterns on planetary surfaces.

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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 have been attempted. The most recent and promising method uses machine learning to train a classifier to recognize dune crests.

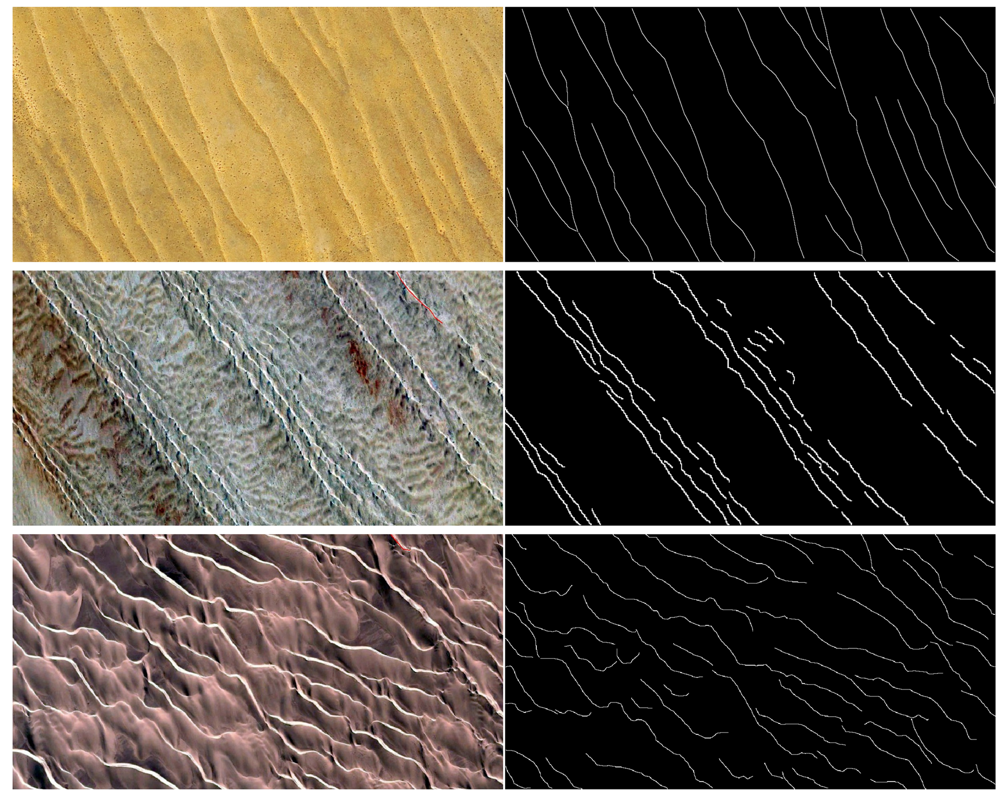
The method applied to each dataset have shown improved reliability and accuracy compared to results published in [4].

Datasets

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.

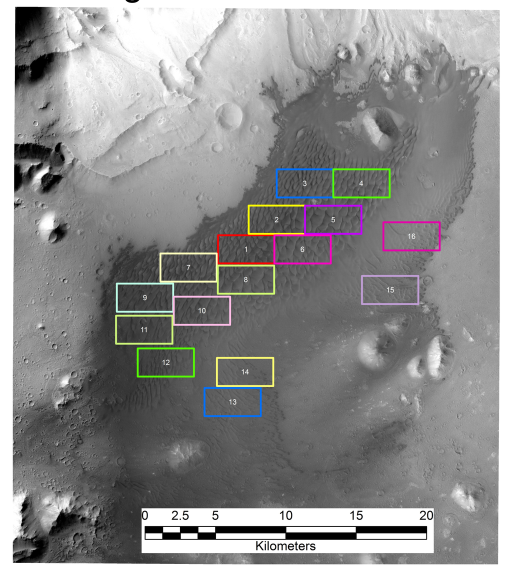
These sample images provide a wide range of examples which makes it an adequate for benchmark testing of various methods.

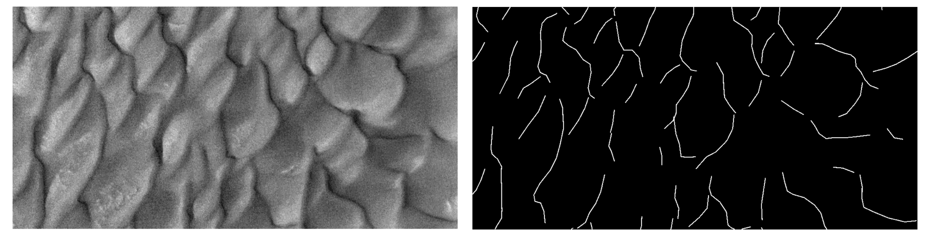


Also, an additional dataset used is from [4]. The dataset includes satellite images from Ganges Chasma and Gale Crater region on Mars. The CTX mosaic which spans an area of 500 km2, includes a wide variety of dune types and morphology.

Aeolian features typically found in this area include sand sheets, dune fields, unidirectional features (such as barchan dunes). The dune fields contain complex sets of diverging dunes which makes it a challenging study area.

The regions are split into sixteen areas of equal size and include labeled ground truth.





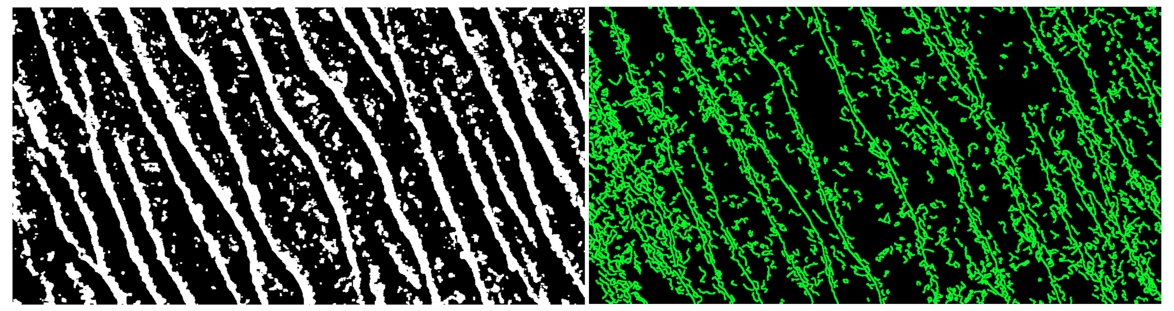
Introduction

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]

Many image processing methods have been attempted to extract these features. A machine learning approach has shown promising results. It consists of extracting features and training a classifier to recognize dune crest-lines from satellite images. We use the popular SIFT features with the Gradient Boosted Tree classifier to train the system. After training, each pixel on the image is classified and given a response score. Higher scores are kept as crest-line candidates, filtered and grouped to form crest-lines.

Methodology

We have explored and implemented many approaches for extracting the crest-lines, including appearance-based segmentation (shown in **A**) by using thresholds to extract bright sides of dunes. Also, gradient-based approaches (shown in **B**) have been used to extract crest-line candidates.



A. **B.**

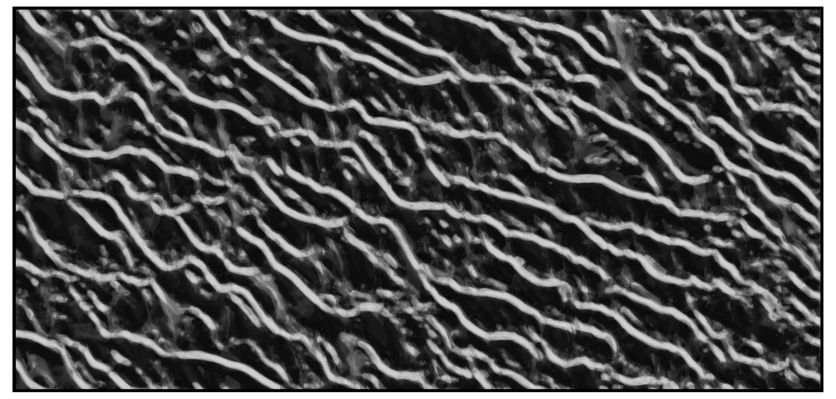
Ultimately, these various approaches require many parameters that need adjustments depending on the types and scales various dunes.

__Machine Learning Approach__: In this approach, the system is trained to recognize dune crest-line patterns. Typically, machine learning methods require training examples to learn from. Images from similar datasets are used to train and test the efficacy of the learning machine.

In order to train the system, features from the same dataset are extracted from the images at known crest-line locations as positive examples, and non-crest-line locations as negative examples.

We use the popular Scale Invariant Feature Transform (SIFT) features to train the classifier. Gradient Boosted Trees have been shown to provide very good training results.

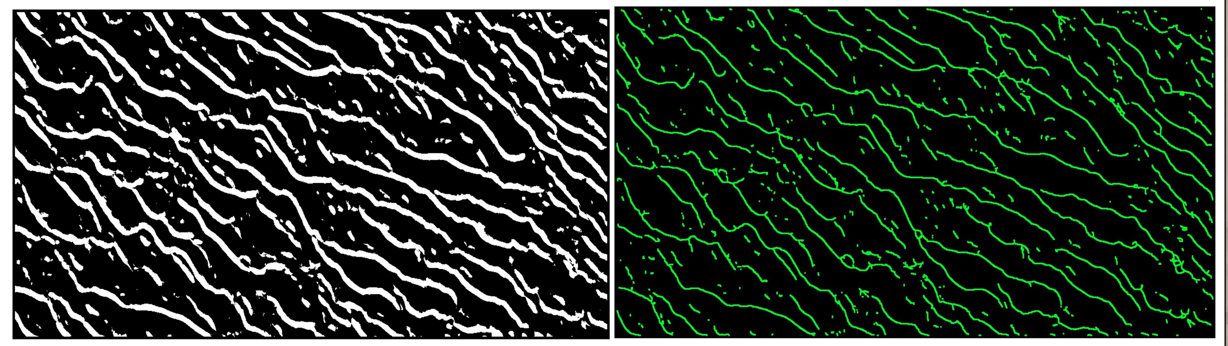
Once the classifier has been trained, classification can be calculated at each pixel in a test image. The response from the classifier is a continuous number between [-1, 1]. A response of -1 represents a non-crest-line pixels, while 1 is considered to be a dune crest-line.



C.

As shown in **C**, bright regions correspond to crest-lines. From the response results of the classification at each pixel, a threshold can be applied to the image into a binary image to remove all non-crest-line pixels.

The resulting binary regions are usually thicker (shown in **D.**). To achieve a thin sharp line on the crest-line, a skeletonization algorithm is applied to the binary image (shown in **E.**).

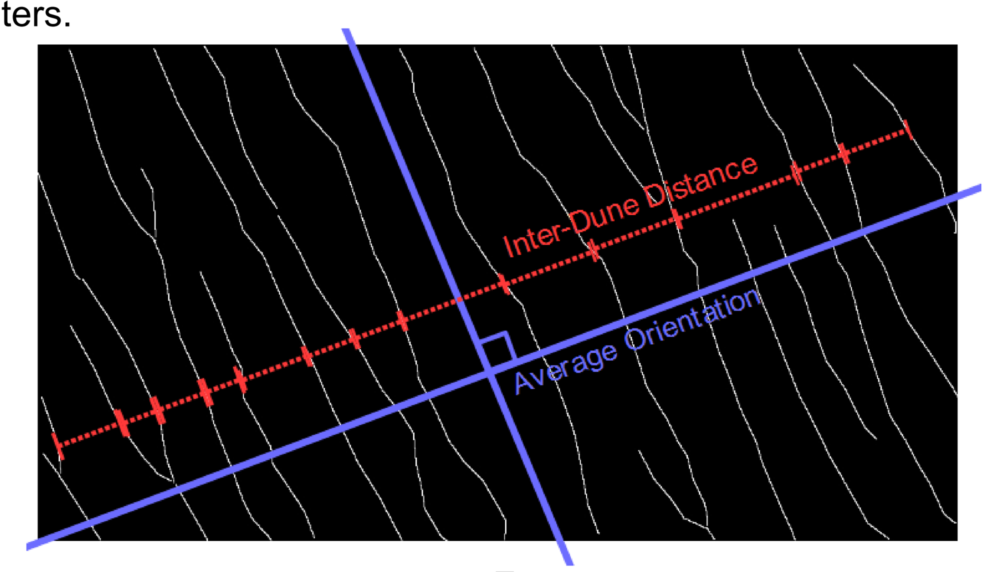


D. **E.**

__Dune Metrics__: The primary goal of finding crest-lines is to extract global geomorphological properties of a given dune-field. There are many metrics that are of value for researchers studying dune field patterns. The two main properties focused in this research are the average orientation of the dune-field, and the average distance between crest-lines. (shown in **F.**).

Computing the average orientation is a relatively simple process once the crest-lines have been detected. Since the detected crest-lines are simply a set of 2D points, a line, or multiple lines can be fitted to each segment from which the orientations are then averaged to determine the overall orientation of the dune field.

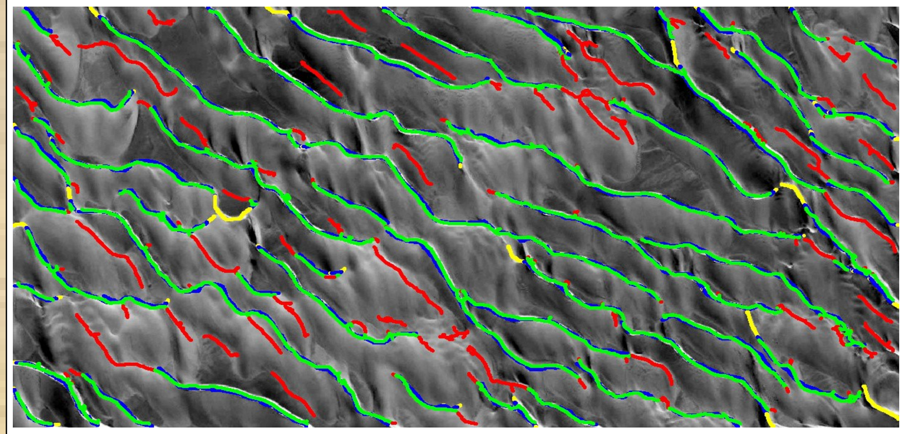
The inter-dune distance is computed by measuring pixel distances (perpendicular to the average orientation) between crest-lines. If the scale of the image is known, the pixel distances can be converted to meters.



F.

Results

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



F.

The results show the correctly identified crest-lines in green on top of the ground truth in blue. Red segments are false positives, while yellow are false negatives.

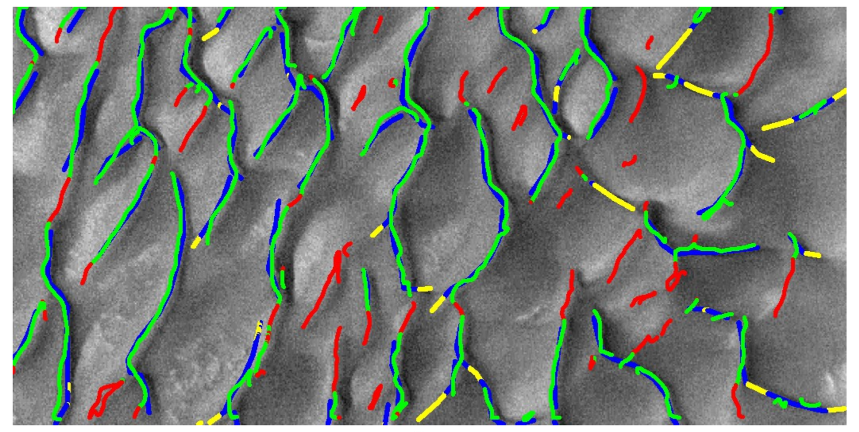
The quality of the results are measured using precision- recall. Recall is a measure of how much of the ground truth was detected, while precision is how many of the detections are correct. A successful detection is determined by a distance e = 5 pixels from a ground truth pixel.

For each image dataset, two sets of images were used. **Set A** was used to train the classifier, and **Set B** was used for testing purposes. This explains the slightly improved results on **Set A**. Typically machine learning methods perform better on examples they have learned on, therefore the results are as expected.

Images	Image Set A		Image Set B	
	P	R	P	R
Kalahari	0.95	0.99	0.90	0.90
Namib	0.95	0.98	0.94	0.84
Simpson	0.95	0.83	0.91	0.83
Skeleton Coast	0.94	0.94	0.98	0.90
WDC	0.97	0.80	0.91	0.80
White Sands	0.98	0.83	0.95	0.79

Table 1.

The results on the Mars dataset (**G.**) are also very impressive. Our method performs significantly better on this dataset compared to the results presented in [4].



G.

Dune metric results shown are achieved by computing the metrics on both the ground truth image and the crest-line detection image. Results show the error between the detection and the ground truth in computing the metrics. Angular error is in degrees and distance error is in pixels.

Images	Image Set A		Image Set B	
	Angle Error	Dist. Error	Angle Error	Dist. Error
Kalahari	0.56	8.45	0.58	9.43
Namib	6.2	2.36	3.53	19.87
Simpson	12.59	9.89	1.01	5.3
Skeleton Coast	0.50	5.27	1.98	16.72
WDC	2.62	6.43	4.05	6.81
White Sands	18.68	10.22	17.02	14.27

Table 2.

Mars Dataset	Vaz [4] Results		Our Results	
	P	R	P	R
Area 1	0.44	0.87	**0.85**	**0.90**
Area 2	0.46	0.91	**0.90**	0.87
	Angle Error	Dist. Error	Angle Error	Dist. Error
Area 1	1.47	55	6.1	**24.5**
Area 2	3.14	61	3.84	**26.16**

Table 3.

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.

It has been shown that the machine learning approach provides much better results than appearance-based or gradient based methods. The drawback of the machine learning method is that it requires a known and well labeled data set to train the classifier.

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.

References

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Acknowledgements

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