

Automated delineation of Martian dune fields

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Introduction

The number of currently available images of the surface of Mars is in the order of the hundreds of thousands. These have been captured over the years by many different instruments on board automatic probes. They have diverse spectral characteristics, varying spatial resolutions and cover areas of different dimensions, providing global, regional and sometimes local views. To manually browse all these images in search of a specific structure of interest is a hard and time consuming process. Thus, our objective is to create a tool that can learn the characteristics of a certain structure in an image and be able to automatically search for it over a huge quantity of data. Currently, we are interested on dune fields, being our approach developed, tested and calibrated for searching those aeolian features on Mars. Dunes fields serve as unique indicators of the interaction between the atmosphere and surface, being among the most widespread aeolian features present on Mars. The study of dune processes contributes to both atmospheric and sedimentary science. Previous works that characterized aeolian features in regional terms conducted manual surveys on image datasets in order to find dune fields. Also, the well established Mars Digital Dune Database was constructed and updated without the use of automated procedures.

Methodology

The methodology is constituted by two main phases and is now applied in the search of dunes fields, independently of its type and also the type of terrain where they may occur. The first phase consists of the extraction of features from their histogram of oriented gradients (RHOG). This method is based on evaluating well normalized local histograms of image gradient orientations in a dense rectangular grid. To obtain these results we used 18 orientation bins over 3x3 block cells

and 51x51 pixels cells, strongly normalized (using Lowe's L2-norm followed by hysteresis thresholding) and with 2/3 overlapping descriptor blocks. In the second phase, the image blocks previously delimited are classified employing the widely used linear Support Vector Machines (SVMs) trained with the freely distributed package *SVMLight* to determine if in fact dunes are present or not in a block image. The parameters used in our case were gamma equal to 2 and C equal to 8.

Results

The method is tested in a set of narrow-angle MOC images that present several types of dune fields that we selected for this purpose. All images are from high latitudes with spatial resolutions better than 5 meters per pixel.

The images were visually analyzed and the dune fields manually contoured, constructing in this way our ground-truth (as it can be seen in the left image of figure 1). Each block was evaluated by intersecting it with the ground-truth and those that had a degree of overlay higher than 0.5 were identified to have dune fields. This formed the basis to train and evaluate the performance of our methodology in quantitative terms. In order to classify the entire image, a 4-fold cross validation was performed (see an example of a classified image in blocks in the right image of figure 1).

The results obtained show that the methodology presented is clearly capable of distinguish dune fields from background: out of the 7482 blocks classified, 7036 were correctly identified (3970 blocks recognized as dunes, true positives, and 3066 as background, true negatives) and only 446 were falsely identified (62 false positives and 384 false negatives), mostly because of the subjectivity of the ground-truth, resulting nonetheless in an overall accuracy of 94 %.

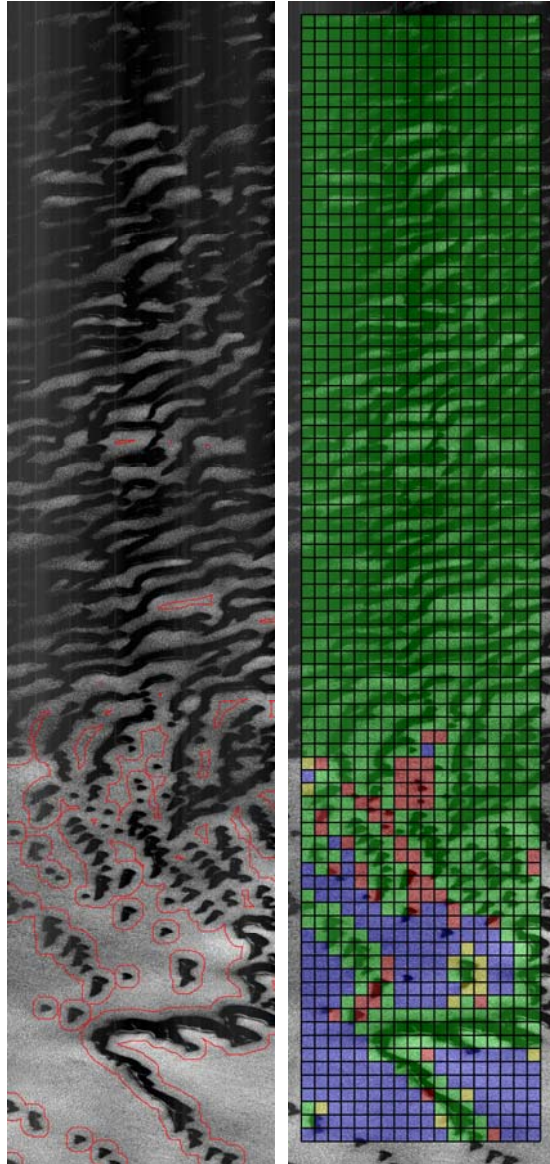


Figure 1 – Left: delineation of dune field by an expert (ground-truth) on MOC image E01-01555; Right: Classification of the image in blocks (green: true positive; blue: true negative, red: false negative, yellow: false positive) (image credits: NASA/JPL/MSSS).

References

- [1] Wilson S.A. and Zimbelman J.R. (2004) *JGR*, 109, E10003.
- [2] Hayward R.K. et al. (2007) *LPS XXXVIII*, Abstract # 1360.
- [3] Dalal N. and Triggs B. (2005) *Proc. CVPR 2005*, vol. 1, 886-893.
- [4] Lowe D.G. (2004) *Int. Jour. Comp. Vision*, 60(2), 91–110.
- [5] Joachims T. (1999) in *Advances in Kernel Methods - Support Vector Learning*, The MIT Press, Cambridge, MA, USA.

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