MARTIAN DUNE FIELDS DETECTION BY AUTOMATED APPROACHES. L. Bandeira[1] , J. S. Marques[2], J. Saraiva[1] and P. Pina[1], [1]CERENA, Instituto Superior Técnico, Av. Rovisco Pais, 1049-001 Lisboa, Portugal (lpcbandeira@ist.utl.pt, jose.saraiva@ist.utl.pt, ppina@ist.utl.pt), [2] ISR, Instituto Superior Técnico, Av. Rovisco Pais, 1049-001 Lisboa, Portugal (jsm@isr.ist.utl.pt).

Introduction: Dunes are the most frequent aeolian features on the Martian surface, and their study contributes to the understanding of the interactions between the atmosphere and the surface of the planet, of the way the climate has evolved along the history of Mars and of how it works currently [1]. At the time of writing, the catalogue of dune fields identified on the surface of Mars by the Mars Dune Consortium [2] contains information about the area between latitudes 65ºS and 90ºN, which is available online in a geographical database, the MGD[3]-Mars Global Digital Dune Database [3, 4]. This represents many hours of manual detection and mapping of aeolian features on thousands of images of the surface of Mars. However, many small fields have yet to be identified and studied in detail.

The development of an automated method for the delineation and characterization of dune fields, capable not only of mapping them on remotely sensed images at different scales and moments in time, but also of detecting changes in the characteristics of these dynamic aeolian features, would thus constitute an important improvement in their study. In the last years, some techniques to automatically detect structures on planetary surfaces have been tried, but, so far, only the field of impact crater studies has achieved some maturity. When it comes to aeolian features, there is as yet no automated approach to deal with their identification, although we have already performed some preliminary tests to verify the adequacy of different automated methods on the detection of ripples [5] and sand dunes [6-7].

Thus, our objective is to use recent and up-to-date machine learning methodologies for the detection of aeolian dunes on remotely sensed images of Mars. This work is partly inspired on some of our previous strategies and algorithmic sequences used for automated crater detection [8].

Methodology: For the purpose now considered, we have selected two types of features that work best in the extraction of the directional and periodic characteristics of the dunes (gradient and histogram-of-oriented-gradients [9] features), and which were both used on Boosting [10] and SVM-Support Vector Machine [11] classifiers to indicate if a given region of the image contains dunes. The performance of those methods is evaluated with a set of high spatial resolution images which reflect the diversity of Martian dune types. A detailed description of these features and of the classifiers can be consulted in [7].

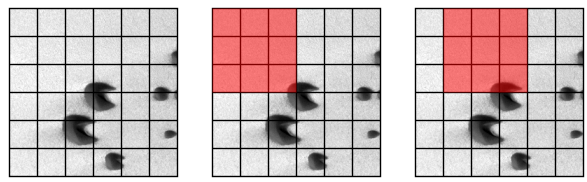


Fig. 1. Principle of evaluation of an image: Tiling in (a) cells and (b) blocks (3x3 cells), in red; (c) Block displacement with overlapping. This region corresponds to a sample of image E02-01086 [image credits: MSSS/NASA/JPL].

Experimental results: To test our approach, we have selected a set of 20 remotely sensed images captured by the Mars Orbiter Camera of the Mars Global Surveyor probe, in N/A mode, from different locations on the planet, covering a total area of about 1320 km^2 and that are representative of the diversity of the most frequent type of dunes (barchan). For each image we constructed ground-truth information, by manually delineating the dunes therein contained, thus indicating the 'dune' and 'not-dune' regions. In the tiling of the ground-truth into cells only the ones containing more than 30% of dune area were considered as 'dune', whereas the cells with less than 10% of dune area were considered as 'not-dune'. The cells with dune areas comprised in the interval 10-30% were not considered.

Every classifier was tested with each of the set of features using a 5-fold cross-validation, i.e., the total number of image blocks was divided into five subsets of the same size: four of them were used for training, the remaining one was used for testing. This procedure was repeated five times, so that each subset is used once for testing.

The performance of each classifier with each set of features is evaluated through the computation of the probabilities of false negatives ($p_{FN} = FN/(FN+TP)$), false positives ($p_{FP} = FP/(FP+TN)$) and of a global error ($p_{error} = p_N . p_{FP} + p_P . p_{FN}$), where FN stands for the number of false negative blocks, TN the number of true negative blocks, FP the number of false positive blocks, TP the number of true positive blocks, N the total number of negative blocks and P the total number of positive blocks.

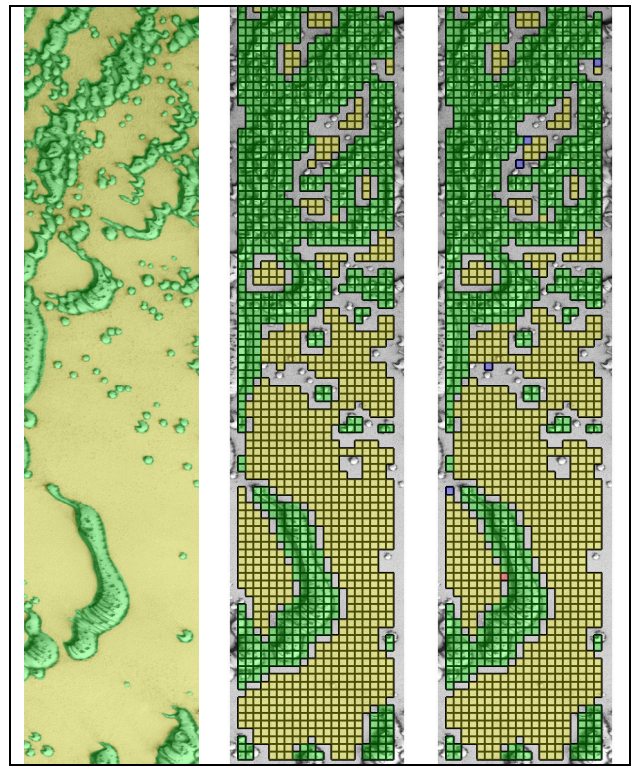
The classification output is illustrated in Fig. 2 with two distinct MOC images. The overall performances obtained for the whole set of images are very good, with the majority of situations presenting probabilities of error (p_{error}) below 0.025.

Conclusions and future work: The major conclusion put forth is the adequacy of automated methods to deal with the diversity of sand dunes on the Martian surface, since many correct detections with significant performances were achieved. Although a set of powerful features and classifiers were successfully used on representative samples of the large diversity of Martian dune fields, we must keep in mind that this is only a preliminary study. We have dealt with dune fields composed by individuals of different sizes, shapes and densities in distinct illumination conditions, but we are aware that many more different situations will have to be faced, namely considering the scale and the diversity of the Martian landscape where many other geomorphological features can and will sometimes be present. Nonetheless, we believe that the adaptive and learning nature of the methods we are using will be able to deal with those different circumstances.

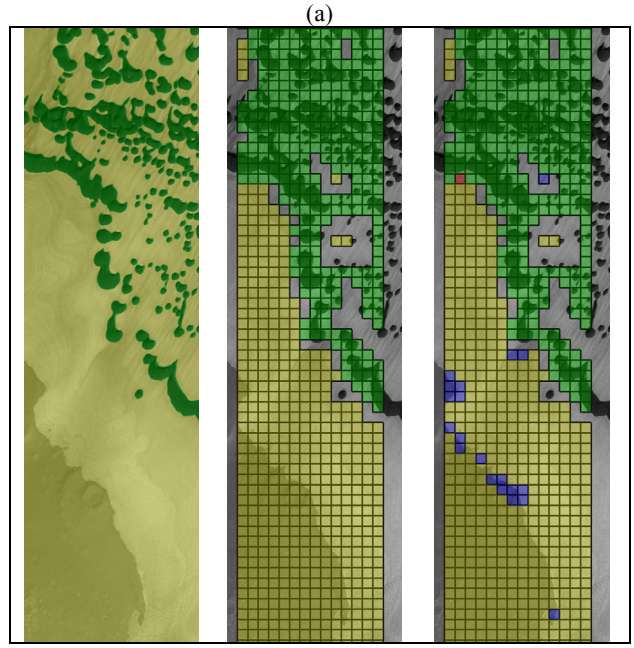
In future work we intend to greatly expand the datasets by incorporating images of every type of Martian dunes and testing on them the approaches we have employed here; we will also test additional types of features and classifiers. Moreover, and with the ultimate goal of making available a robust tool to be used in the cartography of Martian dunes at a planetary scale, we also intend to automatically classify the Martian dunes according to the scheme used in the classification of analogue terrestrial structures [13].

References: [1] Greeley R. et al. (2001) *Spa. Sci. Rev.* 96, 393-404. [2] Hayward R. K. et al. (2007) JGR, 112, E1107. [3] Hayward R. K. et al. (2008) Dunes2008 Abs. # 7013. [4] Hayward R. K. (2010) *LPS XLI* Abs. # 1109. [5] Pina et al. (2004) *LPS XXXV*, abs # 1621. [6] Bandeira et al. (2009) *LPS XL* Abs. # 1288. [7] Bandeira et al. (2010) *LNCS* (in press). [8] Martins R. et al. (2009) *IEEE GRSL* 6(1), 127-131. [9] Dalal N., Triggs B. (2005) *CVPR2005* 886-893, IEEE Press. [10] Viola P., Jones M. (2004) *Int. J. Comp. Vis.* 57(2), 137–154. [11] Vapnik V. N. (1995) *The nature of statistical learning theory*, Springer. [12] Joachims T. (2000) *ICML'2000* 431-438, Morgan Kaufmann Pub. [13] McKee E. D. (1979) *A study of global sand seas*, 1-19, University Press of the Pacific.

Acknowledgements: This work was partially supported by FCT Portugal under the pluriannual fundings of CERENA and ISR. JS (SFRH/BD/37735/2007) and LB (SFRH/BD/40395/2007) acknowledge financial support by FCT Portugal.



(a)



(b)

Fig. 2. Examples of automated dune classification on parts of the images: (a) S01-00925 and (b) R17-00333 (*TP* in green, *TN* in yellow, *FN* in red and *FP* in blue). The images correspond to: (left) input with overlapping of manual ground-truth; (center) ground-truth tiling in cells; (right) output of the classifier [image credits: MSSS/NASA/JPL].