that needs to be generated rather quickly, a combination of watershed based segmentation with either Bagging or SVM is preferable. An application based on such a combination may be useful in cases where maps need to be generated onboard a spacecraft. For a more detailed map, a combination of K-means based segmentation with either Bagging or SVM is recommended. Since the K-means segmentation is slow, applications based on such a combination may be more appropriate for an off-line analysis. Bagging is more sensitive to small local changes in topographic data, and is preferable in applications where high sensitivity is desired; an example is found in maps designed to detect valley networks on Mars. SVM is less sensitive to small changes in topography and produces smoother maps (this is not so evident on the Tisia site, but quite evident on maps from other sites). SVM is preferable in applications where smoother maps are desirable.

Our study also shows the necessity of using a representative training set. Our six test sites are from roughly similar terrains (same geological unit); one would expect that our training set, extracted from a single site, should yield similar results on other sites. This was not the case. A comparison of Tables IV and V indicates that the Tisia site was mapped with higher accuracy than the Vichada site. Also, visual inspection of Fig. 5 shows that the Margaritifer site is poorly mapped, even though it bears topographic similarity to the Al-Qahira site (the former resulting in a good map). Although different sites may have similar landforms, particular characterizations may exhibit different ranges of terrain parameters. As an example, ridges in Al-Qahira and Margaritifer sites look similar, but exhibit different slope magnitudes. Hence, in future applications, we advocate flagging segments labeled with low confidence for additional manual labeling.

We envision two types of spin-off applications. First is an off-line automated data analysis module. Frequently, geological analysis consists of a descriptive comparison among maps (of two or more sites) in order to identify similarities and/or differences in the presence and character of selected landforms. Because our methodology produces digital thematic maps of landforms, such maps can be subjected to machine-assisted comparison (see, for example [31], [32]). Second is an onboard application that generates geomorphic maps for the purpose of data compression. Such maps can be cheaply transmitted to Earth to assist ground controllers in decision making. Future work will address faster algorithms for quality segmentation (to replace the slow K-means algorithm), development of additional topography-derived features, incorporating imagery data to add texture information, and a robust approach to incorporate context information (e.g., using Markov Random Fields).

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References

[1] R. Adams and L. Bischof. Seeded region growing. *IEEE Transactions on Pattern Analysis Machine Intelligence*, 16(6):641–647, 1994.

[2] L. Bandeira, J. Saraiva, and P. Pina. Impact crater recognition on mars based on a probability volume created by template matching. *IEEE Transactions on Geoscience and Remote Sensing*, 45(12):4008–4015, December 2007.

[3] T. Barata, E. I. Alves, J. Saraiva, and P. Pina. Automatic recognition of impact craters on the surface of mars. In *Image Analysis and Recognition*, volume 3212 of *Lecture Notes in Computer Science*, pages 489–496. Springer Berlin / Heidelberg, 2004.

[4] S. Belongie, C. Carson, H. Greenspan, and J. Malik. Color- and texture-based image segmentation using EM and its application to content-based image retrieval. In *Proceedings of the Sixth International Conference on Computer Vision*, 1998.

[5] S. Beucher. The watershed transformation applied to image segmentation. *Scanning Microscopy International*, (6):299–314, 1992.

[6] B. E. Boser, I. Guyon, and V. Vapnik. A training algorithm for optimal margin classifiers. In *Computational Learning Theory*, pages 144–152, 1992.

[7] L. Breiman. Bagging predictors. *Machine Learning*, 24(2):123–140, 1996.

[8] B. D. Bue and T. F. Stepinski. Machine detection of martian impact craters from digital topography data. *IEEE Transactions on Geoscience and Remote Sensing*, 45(1):265–274, 2007.

[9] M. C. Burl, T. Stough, W. Colwell, E. B. Bierhaus, W. J. Merline, and C. Chapman. Automated detection of craters and other geological features. In *6th International Symposium on Artificial Intelligence, Robotics and Automation in Space Montreal, Canada*, June 2001.

[10] Y. Cheng, A. E. Johnson, L. H. Matthies, and C. F. Olson. Optical landmark detection for spacecraft navigation. In *AAS/AIAA Astrodynamics Specialist Conference Puerto Rico*, Feb 2003.

[11] Y. Deng and B. S. Manjunath. Unsupervised segmentation of color-texture regions in images and video. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23(8):800–810, 2001.

[12] T. G. Dietterich. Ensemble methods in machine learning. *Lecture Notes in Computer Science*, 1857:1–15, 2000.

[13] L. Dragut and T. Blaschke. Automated classification of landform elements using object-based image analysis. *Geomorphology*, 81:330 – 344, 2006.

[14] H. Feng, D. A. Castanon, and W. C. Karl. A curve evolution approach for image segmentation using adaptive flows. *International Conference on Computer Vision*, 02:494, 2001.

[15] A. L. Gallant, D. D. Brown, and R. M. Hoffer. Automated mapping of hammond's landforms. *IEEE Geoscience and Remote Sensing Letters*, 2(4):384–288, 2005.

[16] T. Hengl. *Pedometric mapping: bridging the gaps between conventional and pedometric approaches*. PhD thesis, Wageningen University, 2003.

[17] R. Honda, Y. Iijima, and O. Konishi. Mining of topographic feature from heterogeneous imagery and its application to lunar craters. In *Progress in Discovery Science, Final Report of the Japanese Discovery Science Project*, page 395407, London, UK, 2002. Springer-Verlag.

[18] F. Jing, M. Li, H. Zhang, and B. Zhang. Unsupervised image segmentation using local homogeneity analysis. In *IEEE International Symposium on Circuits and Systems*, 2003.

[19] G. H. John and P. Langley. Estimating continuous distributions in bayesian classifiers. In *Eleventh Conference on Uncertainty in Artificial Intelligence, San Mateo*, pages 338–345, 1995.

[20] J. John H. Lowry, R. Ramsey, K. Boykin, D. Bradford, P. Comer, S. Falzarano, W. K. J. Kirby, L. Langs, J. Prior-Magee, G. Manis, L. O'Brien, K. Pohs, W. Rieth, T. Sajwaj, S. Schrader, K. A. Thomas, D. S. K. Schulz, B. Thompson, C. Wallace, C. Velasquez, E. Waller, and B. Wolk. Final report on landcover mapping methods. Technical report, The southwest regional gap analysis project, october 2005.

[21] J. Kim, J. Muller, S. van Gasselt, J. Morley, G. Neukum, and t. Team. Automated crater detection, a new tool for mars cartography and chronology. *Photogrammetric Engineering and Remote Sensing*, 71(10):1205–1217, October 2005.

[22] D. Landgrebe. The Evolution of Landsat Data Analysis. In *Photogrammetric Engineering and Remote Sensing*, pages 859–867, 1997.

[23] D. Landgrebe. *Information Extraction Principles and Methods for Multispectral and Hyperspectral Image Data*, chapter 1. Information Processing for Remote Sensing,World Scientific Publishing Co, 1999.

[24] B. Leroy, G. Medioni, E. Johnson, and L. Matthies. Crater detection for autonomous landing on asteroids. *Image and Vision Computing*, 19(11):787 – 792, September 2001.