

# Implementation of an On-Board Terrain Classifier based on Proprioceptive Sensor Data for a Planetary Rover

Raul Dominguez<sup>1</sup>, Lennart Kuhr<sup>2</sup>, Jonathan Babel<sup>1</sup>, Florian Cordes<sup>1</sup>, Giulio Reina<sup>3</sup>, and Frank Kirchner<sup>1,4</sup>

<sup>1</sup>DFKI Robotics Innovation Center Bremen Robert-Hooke-Str. 1, 28359 Bremen, Germany,  
E-mail: name.surname@dfki.de

<sup>2</sup>Institute of Space Systems, TU Braunschweig, Herman-Blenc-Straße 23, 38108 Braunschweig, Germany,  
E-mail: l.kuhr@tu-braunschweig.de

<sup>3</sup>Department of Mechanics, Mathematics and Management, Polytechnic of Bari, Via Orabona 4, 70125, Bari, Italy,  
E-mail: giulio.reina@poliba.it

<sup>4</sup>Robotics Research Group, University of Bremen, Germany

Planetary explorations missions are so far dominated by wheeled rover designs like Curiosity or Perseverance [MJR<sup>+</sup>21, WLM13]. Although wheeled locomotion is most energy-efficient over flat terrain, it compromises drawbacks when exposed to demanding unstructured terrain. Especially in unstructured environments with steep, sandy slopes and boulders patches, wheeled systems reach their limitations [Kol21]. In the past, several high slip and excessive sinkage events have been encountered with exploration rovers, which have severely disrupted the mission timeline [GI18]. For example, it took five weeks to free the Opportunity rover from sand in 2006 [You06], and rover trajectories are frequently adjusted to avoid challenging terrain [AIM<sup>+</sup>17]. The potentially worst situation occurred in 2009 when the Spirit rover got stuck in the sand and was unable to recover, ultimately ending the mission [WM09]. Terrain awareness, the correct modeling of the surfaces transited and its classification is a key factor for reliable autonomous navigation and environment modelling. An appropriate surface modelling can be used to avoid rover navigation operations problems as the ones described before. Moreover, terrain awareness can be used to enhance navigation capabilities by adapting system settings in accordance to the terrain properties.

In this publication a software component implementation capable of classifying the traversed terrain type based on proprioceptive sensor data is presented. The component uses a Support Vector Machine (SVM) algorithm [BGV92, CST00] in its core. It is integrated into the software control architecture of the mobile exploration robot SherpaTT, such that it can be executed sufficiently fast during navigation. SherpaTT is a hybrid wheeled-leg rover with an actively articulated suspension system. Its locomotion control system provides the basis for advanced locomotive capabilities with the ability to adapt to different terrain types [CKB18]. The novel software component has been implemented using the framework Robotic Construction Toolkit (Rock)<sup>1</sup>. The diagram in Figure 1 presents the implementation approach of the terrain classifier in Rock.

One of the main challenges addressed by the middleware component is to generate matrices of synchronous sample values for classification online from datastreams with multiple frequencies. During navigation the terrain classifier uses force torque sensors, joint data and body acceleration estimates to classify the surface into one of three terrain types: *sand*, *compact sand* and *concrete*. The three types represent distinct classes of surfaces characterized by its deformability and friction properties, but are hard to identify with exteroceptive sensors since they are visually similar. In order to achieve a better classification performance as well as a more in-depth characterization of the surface patches, a feature calculation process is performed. The computed features estimate physical properties such as mechanical power, electrical power, friction coefficients and speed deviation. Along with all of these features, the corresponding statistical values, i.e. variance, skewness and kurtosis are evaluated. Finally, critical features for terrain classification must be identified to reduce the dimensionality of inputs to the classifier. This feature selection process was done using a WB index and the Pearson Coefficient as detailed in [DCR20]. Furthermore, the classification results need to be available at a fast enough pace to allow other onboard components take advantage of the results (e.g. to improve

---

<sup>1</sup>Rock: The Robot Construction Kit (<http://rock-robotics.org>)

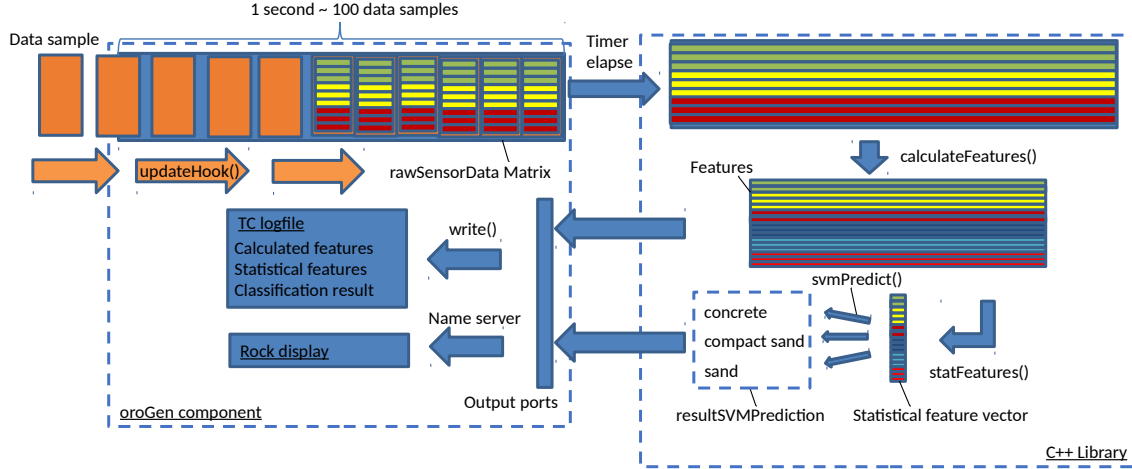


Figure 1: Overview of the terrain classifier library and Rock integration.

navigation) and to ensure that the classification results correspond to the currently traversed surface. Likewise, the loss of data samples due to full queues on the input of the processing components must be avoided.

The initial offline evaluation of the SVM classifier reached an accuracy of 93.97% as shown in the confusion matrix in Figure 2. Results generated from several test traverses of SherpaTT were logged to analyze the onboard classification performance and compared with the ones obtained from training sets. A complete analysis of performance was not possible, because the traversed terrain during the field tests did not closely match the previously trained terrain classes. Nevertheless, the software shows good classification results, since the type of surface *-wet compact sand-* was close to the two classes mostly identified *-concrete* and *compact sand*. Several field tests demonstrated that the terrain classifier can be executed on SherpaTT and that it is able to compute features as well as classify different terrain types successfully, whilst the rover is traversing the surface. The C++ calculations and terrain classifications were executed in sufficient time in parallel to the rest of SherpaTT's Motion Control System, on a single thread, using a i7 processor with a CPU clock speed of 4.6 GHz.

Actual	concrete	136 29.31%	0 0.0%	3 0.65%	139 97.84% 3.14%
	compact sand	8 1.72%	191 41.16%	17 3.66%	216 88.43% 11.57%
	sand	0 0.0%	0 0.0%	109 23.49%	109 100% 0.0%
	sum_col	144 94.44% 5.56%	191 100% 0.00%	129 84.50% 15.50%	464 93.97% 6.03%
		Predicted			
		concrete	compact sand	sand	sum_lin

Figure 2: Shows the performance of the SVM model. Except the recall for *compact sand* and the precision for *sand* all performances are above 90%, with an overall accuracy of 93.97%

## References

- [AIM<sup>+</sup>17] Raymond E. Arvidson, Karl D. Iagnemma, Mark Maimone, Abigail A. Fraeman, Feng Zhou, Matthew C. Heverly, Paolo Bellutta, David Rubin, Nathan T. Stein, John P. Grotzinger, and Ashwin R. Vasavada. Mars Science Laboratory Curiosity Rover Megaripple Crossings up to Sol 710 in Gale Crater. *Journal of Field Robotics*, 34(3):495–518, 2017. [\\_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/rob.21647](https://onlinelibrary.wiley.com/doi/pdf/10.1002/rob.21647).
- [BGV92] Bernhard E. Boser, Isabelle M. Guyon, and Vladimir N. Vapnik. A training algorithm for optimal margin classifiers. In *Proceedings of the Fifth Annual Workshop on Computational Learning Theory, COLT '92*, page 144–152, New York, NY, USA, 1992. Association for Computing Machinery.
- [CKB18] Florian Cordes, Frank Kirchner, and Ajish Babu. Design and field testing of a rover with an actively articulated suspension system in a mars analog terrain. *Journal of Field Robotics*, 35(7):1149–1181, 2018.
- [Cow05] Ron Cowen. Opportunity rolls out of purgatory. 167(26):413, 2005.
- [CST00] Nello Cristianini and John Shawe-Taylor. *An Introduction to Support Vector Machines and Other Kernel-based Learning Methods*. Cambridge University Press, 2000.
- [DCR20] Mauro Dimastrogiovanni, Florian Cordes, and Giulio Reina. Terrain estimation for planetary exploration robots. *Applied Sciences*, 10(17), 2020.
- [GI18] Ramon Gonzalez and Karl Iagnemma. Slippage estimation and compensation for planetary exploration rovers. State of the art and future challenges. *Journal of Field Robotics*, 35(4):564–577, 2018. [\\_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/rob.21761](https://onlinelibrary.wiley.com/doi/pdf/10.1002/rob.21761).
- [Kol21] Hendrik Kolvenbach. *Quadrupedal Robots for Planetary Exploration*. PhD thesis, June 2021.
- [MJR<sup>+</sup>21] Robert C. Moeller, Louise Jandura, Keith Rosette, Matt Robinson, Jessica Samuels, Milo Silverman, Kyle Brown, Elizabeth Duffy, Aaron Yazzie, Elizabeth Jens, Iona Brockie, Lauren White, Yulia Goreva, Torsten Zorn, Avi Okon, Justin Lin, Matthew Frost, Curtis Collins, Jeffrey B. Williams, Adam Steltzner, Fei Chen, and Jeff Biesiadecki. The sampling and caching subsystem (scs) for the scientific exploration of jezero crater by the mars 2020 perseverance rover. *Space Science Reviews*, 217(1):5, 2021.
- [WLM13] Richard Welch, Daniel Limonadi, and Robert Manning. Systems engineering the Curiosity Rover: A retrospective. In *2013 8th International Conference on System of Systems Engineering*, pages 70–75, Maui, HI, USA, June 2013. IEEE.
- [WM09] G. Webster and V. McGregor. NASA’s Mars Rover has Uncertain Future as Sixth Anniversary Nears, 2009.
- [You06] Kelly Young. Mars rover escapes from the bay of lamentation, 2006.