SLIP PREDICTION FOR PLANETARY ROVER TRAVERSABILITY ASSESSMENT USING ORBITAL IMAGERY

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Abstract

Terrain trafficability (and consequently, vehicle traversability) is an important factor in planetary rover missions. Terrain trafficability is defined as the ability of a terrain to sustain the traversal of a mobile vehicle (Papadakis, 2013; Muro, 2004). It depends on the rover itself and factors such as terrain properties and topography. Currently, the trafficability assessment mostly depends on on-board images taken from the previous sol (Martian day), with which making a reliable assessment on the surface beyond a few tens of meters from the current position is difficult. Orbital images are also used to assess the drivability beyond this distance, but it is hard to make a reliable prediction on key trafficability metrics, such as slip, due to its limited resolution. To improve predictions over extensive distances and to support ground assessment of the terrain, this paper proposes a method to support slip assessment from thermal inertia measured by orbital observations. More specifically, the proposed model takes thermal inertia maps and digital elevation models as inputs and predicts whether slip is less than 30% or greater. Thermal inertia translates the ability of a material to store heat during the day and release it at night, and depends on various terrain properties (e.g., grain size, conductivity), that could affect trafficability. In general, the lower the thermal inertia, the lower the trafficability, and vice versa (Cunningham, 2017). These results confirms that thermal inertia plays an important role in predicting slip and could improve terrain trafficability assessment significantly. Other data sets were also tested in combination with thermal inertia and slope, such as terrain types and rock abundance, but it did not significantly change the performance of the model. The contribution of this work is to incorporate thermal inertia to slip prediction, producing a model that can give results covering great distances, and could be key to safer missions.

Keywords: Slip Prediction, Mars Rover, Trafficability, Orbital Data, Thermal Inertia, Slope

1. Introduction

Terrain trafficability is an important factor in all planetary rovers, especially as future surface missions become more complex and aim at going further into the solar system (Lorenz et al., 2018). These missions require autonomy in robotics as it would enable driving beyond line-of-sight (i.e., beyond what is seen on images received from the planet's surface), ensure safety at every step, and allow more complex designs to be put together with restricted budget and staffing (Fong et al., 2017). Trafficability is defined as the ability for a given terrain to sustain the traversal of a mobile robot without reaching failure and involves studying the robot's response to the terrain it is driven on (Papadakis, 2013). While trafficability is a terrain characteristic, this work also mentions traversability, which is the ability of a vehicle to traverse a terrain. The two are used throughout this paper, depending whether the rover or the terrain is considered.

For planetary surfaces, the terrain is not always known and research has focused for years on ways to assess trafficability and traversability with limited information. After the loss of the rover Spirit at Gusev Crater in 2010, it has become even more important to understand terrain properties and how vehicles interact with the ground on remote worlds. Spirit traversed compacted terrain at the beginning while on Gusev plains, however, upon arriving at the Columbia Hills, it encountered highly deformable sulfate rich soil that made traversability a challenge (Johnson et al., 2015). Moreover, these soils were covered in basaltic sand, making them invisible to the team planning the traverse. The rover underwent high sinkage (up to 10 cm), and the failure of the right front wheel actuator made the traverse even worse as Spirit was forced to drag its wheel along. It eventually got embedded in a sand filled crater when the left side of the rover tilted into the crater and the wheel got stuck (Johnson et al., 2015). Failure to extricate Spirit led to the end of its mission in 2010. Opportunity encountered high wheel sinkage situations as well, at Endeavour Crater, when it came across the Purgatory ripple field (Arvidson et al., 2011) and Curiosity experienced mobility difficulties with wheel damage (holes and dents) from roving on sharp rocks (Arvidson et al., 2017).

Terramechanics, i.e., vehicle-terrain interaction mechanics, has been identified as a way to assess trafficability given the constraints of planetary missions, and more specifically, the interaction of the rover's wheels with the surface can potentially provide answers to the question of trafficability. Understanding the terrain and its interaction with Curiosity's wheels may have prevented any damage, and there is a recognized need to incorporate terramechanics to planning to prevent mobility issues (Arvidson, 2014). Early in the application of terramechanics to planetary rovers, some variables have been identified as necessary for exploration missions, such as slip (Ding et al., 2011). The authors point out the necessity of estimating the amount of slip encountered by the rover, given the limited onboard computational resources. Slip is highly related to terrain trafficability: limited slip could indicate traversable areas, and high slip could point to difficult if not untraversable areas. Most importantly, high slip can lead to the rover getting embedded, temporarily trapped, as did Curiosity on sol 672 (Bouguelia et al., 2017), or not being able to recover, as demonstrated by Spirit (Johnson et al., 2015).

As NASA prepares for its very next rover mission to Mars, Mars 2020, it is important to understand how the Perseverance Rover would potentially behave when roving on the regolith at Jezero Crater, the chosen landing site (NASA, 2018). The goal of this research is to assess slip using orbital imagery available, leading to prediction over extensive areas that could support ground-based terrain trafficability assessment. This paper is organized as follows: after detailing related research, the problem statement of this work will be presented, followed by the technical approach. Results and conclusion will be presented next.

2. Related Work

As previously mentioned, terrain trafficability is an important factor to take into consideration in preparation for the next Mars mission, Mars 2020. During the lunar era, missions such as Lunakhod and Apollo sent instruments to the Moon to assess the terrain and its trafficability (Zacny et al., 2010). Since, research has been published that uses terramechanics to assess the terrain in real time, and includes a wide range of techniques, from the use of wheels and sensors to actual instruments (Chhaniyara et al., 2012). For example, a terrain classifier has been proposed that uses the vibrations induced in the vehicle by the wheel-terrain interaction during a drive (Brooks & Iagnemma, 2005) to identify terrains and assess their safety with regards to driving. Another model was proposed to identify key terrain properties using on-board sensors and estimate traversability from these parameters (Iagnemma et al., 2004). Both models assess traversability while driving, which makes predictability for long distances a challenge. To remedy this issue, other methods have been proposed, such as simulations offline of traverses on a user-defined terrain with a software called ARTEMIS (Adams-based Rover Terramechanics and Mobility Interaction Simulator). This software has been validated with a single wheel experiment (Senatore et al., 2014), as well as tests in the JPL Mars Yard and field experiments in the Mojave Desert (Zhou et al., 2014, 2017). It has then been used to simulate traverses for the Opportunity and Curiosity rovers. However, since orbital imagery is usually not enough to fully characterize a terrain (Gaines et al., 2016), this method requires ground data and is therefore limited to the few tens of meters ahead of the rover, where terrain parameters can be assessed more precisely. More recently, several authors have looked into predicting better traverse performance by taking into account orbital data such as HiRISE (High Resolution Imaging Science Experiment) or slope in a software called Mars Terrain Traversability Tool (Ono et al., 2016). MTTT uses a terrain classifier, Soil Property and Object Classification (SPOC) that analyses HiRISE images to classify different terrains into different categories

(Rothrock et al., 2016). These terrain types are coupled with rock abundance (Cumulative Fractional Area (Golombek & Rapp, 1996) or CFA), hazards and slope to predict rover speed (Ono et al., 2016).

Some other terrain trafficability prediction models use slip to directly assess the safety of driving (Ding et al., 2009). Slip is an important aspect of terrain trafficability and has been the subject of many studies (Senatore et al., 2014; Johnson et al., 2015). It is a response of the wheels driving on a surface (e.g., sandy, steep) and is highly related to the terrain type. Intuitively, high slip lowers trafficability, as seen with Spirit when its wheels reached 100% slip (Johnson et al., 2015), and vice-versa. Tests to analyze slip behaviors for MERs on different slopes were conducted in the laboratory (Biesiadecki et al., 2006). Several models for slip have been proposed, especially in the foundation work of terramechanics (Bekker, 1969; Wong et al., 1989), but it is not until later that predicting slip has been attempted and used as a mean of assessing terrain trafficability. For example, some authors have proposed a model that utilizes on-board cameras to remotely classify terrains, predict slip and plan the path given the three terrain categories: traversable, not traversable, and uncertain. This system has been specifically intended for planetary rovers after seeing the difficulties encountered on Mars (Helmick et al., 2008). Another prediction model uses visual information from the rover itself (e.g., stereo images) to give an estimate of slip on forthcoming terrains (Angelova et al., 2007; Angelova, 2008) to help identify safer paths. Later, thermal inertia has been suggested as a tool to assess slip, using both the Ground Temperature Sensor (GTS) onboard Curiosity (Sebastián et al., 2010) and the Thermal Emission Imaging Spectrometer (THEMIS) onboard the satellite Mars Odyssey (Christensen et al., 2004). The results from rover-based and orbital analysis show that thermal inertia greatly helps in improving slip predictions given slope, and that overall, lower slip is correlated with decreased thermal inertia (Cunningham, 2017). Most of slip prediction methods, however, utilize on-board resources and do not rely solely on orbital imagery.

3. Problem statement and contribution

The main goal is to provide a method that predicts ranges of slip for a Mars rover in order to facilitate and support ground terrain trafficability assessment, using only information available *a priori*, i.e., orbital data. Terrain information publicly available includes topography, (Digital Elevation Models or DEMs via HiRISE, the High Resolution Imaging Science Experiment), thermal inertia and slip data for both Mars Exploration Rovers (MER), i.e., Spirit (MERa) and Opportunity (MERb). In addition, other information available for this study include rock abundance (Golombek & Rapp, 1996) or CFA (Cumulative Fractional Area) and terrain types (Rothrock et al., 2016); however, these information are only available at Gusev Crater (MERa landing site). The main constraint for this research is the limited amount of data available, that is, the analysis is limited to the length of the traverses, the orbital coverage over the traverses, and the slip checks performed along the way. The main challenge is to reconcile the data to obtain values of slope, thermal inertia and slip, as well as terrain types and CFA when available, at measurement points. It is assumed that this method can be applied to other landing sites on Mars for other rovers (e.g., Perseverance).

The contributions of this work are the following: 1) to propose a method that allows for direct prediction of slip using orbital data only; 2) to provide a mean of predicting slip that can support ground terrain assessment; and 3) to give trafficability information over extended distances, as long as the orbital coverage is available, which means that a path can be analyzed with greater certainty prior to the mission landing.

4. Technical approach

4.0.1. Orbital Data

Thermal inertia can be used for terrain trafficability analysis as it brings information about the surface and subsurface. It is derived from the Mars Odyssey Thermal Emission Imaging System (THEMIS) nighttime temperatures (Fergason et al., 2006) and depends on several factors including particle size, degree of induration, rock abundance and exposure of bedrock at the subsurface (within a few centimeters of the surface). It translates the ability of a material to store heat during the day and release it at night (Putzig et al., 2005) and is defined as follows:

$$I = \sqrt{k\rho c} \tag{1}$$

Where I is the thermal inertia in thermal inertia unit (TIU, 1 $TIU = 1\ Jm^{-2}K^{-1}s^{-1/2}$), k is the bulk thermal conductivity, ρ is the bulk density and c is the specific heat of the surface layer (up to a few centimeters below the surface (Putzig et al., 2005)). In general, given that thermal inertia is directly proportional to the bulk density and therefore compaction and bearing strength, low values are associated with deep sand, leading to harder conditions for a rover to drive, whereas high thermal inertia translates into indurated material such as bedrock. This implies that the rover would have less difficulty driving on terrains displaying higher values of thermal inertia (Cunningham, 2017). The thermal inertia data set has a resolution of 100 m/pixel (Fergason et al., 2006). Thermal inertia has been used in the past to understand surface properties (Putzig & Mellon, 2007) and has been considered for slip predictability and trafficability assessment (Cunningham, 2017).

Slope also plays a significant role in terrain trafficability. The Mars Exploration Rovers (MERs) avoided slope greater than 30° due to potential sliding on steeper slope (Biesiadecki et al., 2006). Testing has been conducted to understand trafficability on different slopes for Spirit and Opportunity (Lindemann & Voorhees, 2005) and Curiosity (Heverly et al., 2013). Slope is obtained from Digital Elevation Models (DEMs) over selected areas, which have a resolution of 1m/pixel. Slope is derived from the gradient of the height from the DEM times the heading angle in the rover's direction as shown in Eq.(2).

$$S = \begin{pmatrix} \frac{\partial h}{\partial x} \\ \frac{\partial h}{\partial y} \end{pmatrix} \cdot \begin{pmatrix} cos\theta \\ sin\theta \end{pmatrix} \tag{2}$$

Where h is the height given by the DEM, (x, y) are the coordinates of the location for which slope is calculated (pixel of 1 square meter), and θ is the heading angle. The slope is calculated at the (x, y) location by deriving the gradient for the average height over 9 pixels (the pixel (x, y) and the 8 surrounding pixels).

In addition to thermal inertia and slope available at both sites, the SPOC software generated a terrain type map for Gusev Crater (Rothrock et al., 2016) and the associated CFA coverage (Golombek & Rapp, 1996) was made available for this study.

4.1. Principal Component Analysis (PCA)

Table 1: Principal Component Analysis (PCA) results showing PC (Principal Components) 1 to 4 with the contribution of each variable (in %).

	PC1	PC2	PC3	PC4
Variance explained	***46.51%***	***28.21%***	***14.83%***	***10.46%***
Thermal inertia	6.250%	65.62%	14.78%	13.35%
Slope	19.82%	30.70%	44.60%	48.80%
Terrain types	34.94%	0.9800%	40.55%	23.53%
CFA	38.99%	2.710%	0.07450%	58.23%

To better understand the role of slope and thermal inertia, a Principal Component Analysis (PCA) on all four variables (thermal inertia, slope, terrain types and CFA), centered and standardized, is performed at Gusev Crater. It revealed that the first three components contribute to 89.54% of the data, almost 90%, and the first two alone contributes to 74.71% of the data, almost 75%. The biplot shown in Fig.1 shows that if terrain types and CFA contribute the most to PC1, slope and thermal inertia contribute the most to PC2 and most importantly, to the total explained variance by dimension one and two, at 53.70% and 39.23% respectively (Fig.1). Thermal inertia and slope are thus retained as the main contributing variables and the predictors needed for slip analysis.

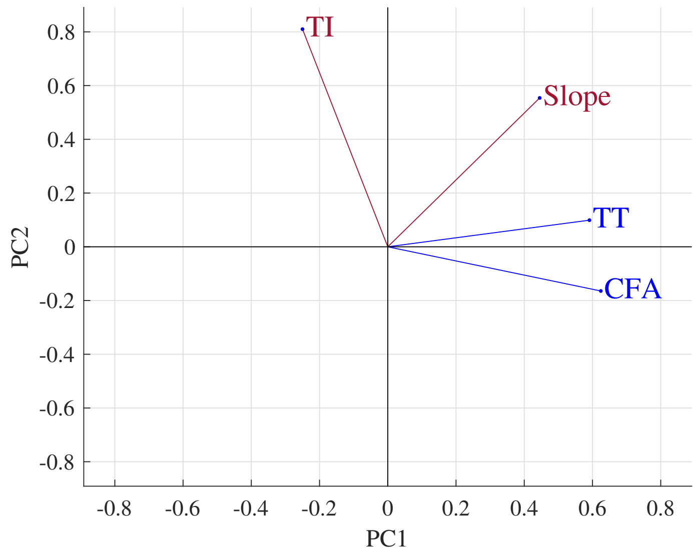


Fig. 1: *Biplot showing the contribution of each variable to the first two PCs that explain 75% of the data. TI: thermal inertia; TT: terrain types; CFA: cumulative fractional area.*

4.2. Data points available

The data are taken from both the Opportunity and Spirit rovers, at Meridiani Planum and Gusev Crater, respectively. Slip was recorded only when Visual Odometry (VO) was enabled - called "slip checks" (Maimone et al., 2007). However, VO was not always an option since it did not allow for fast speed (Biesiadecki et al., 2007), and consequently, few data points were available for this study, as shown in 2. 2073 data points were collected for Spirit (MER A, Fig.2b) and 3250 for Opportunity (MER B, Fig.2a, processed DEM coverage is not available everywhere at Meridiani Planum).

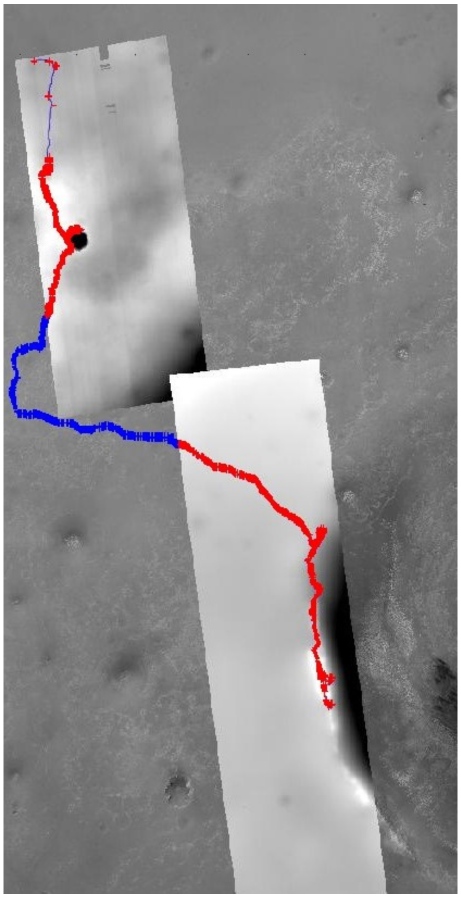
4.3. Data processing

If slope has been identified for a long time as a factor for slip experienced by rovers (Bouguelia et al., 2017), the role of thermal inertia was not as clearly defined until recently (Cunningham, 2017). It is related to terrain properties as shown in section 4.0.1 and is important with regards to predicting slip.

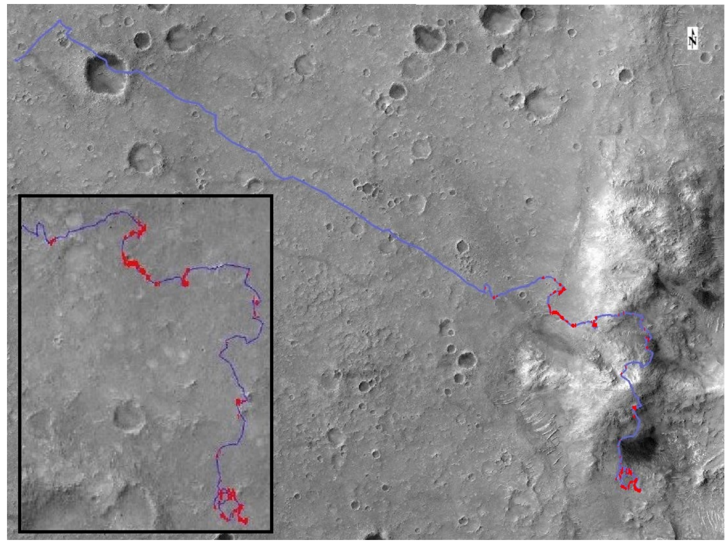
The slope and thermal data were combined to train a classifier to predict ranges of slip: lower than 30% or higher than 30%. This threshold was taken from a similar classification used in Bouguelia et al. (2017) with classes medium slip ($30-60\%$) and high slip ($> 60\%$) combined into one category. While their work focuses on tracking ranges of slip from ground data and rover behavior, this research aims at producing a classifier that will allow slip prediction exclusively from orbit. In order to obtain the value for slope and thermal inertia at the location of the slip value, the raw data were georeferenced and longitude and latitude for each pixel of the maps were obtained. Similarly, slip checks coordinates in terms of latitude and longitude were computed along the traverse. And finally, the height from the DEM at each pixel was converted to slope by averaging the values over the height surrounding pixels and deriving the gradient in the rover direction.

4.4. Classifier training

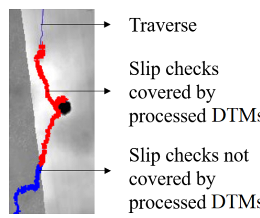
Once the matrix of slope, thermal inertia and slip values at measurement locations was obtained, the data were prepared for training a classifier. It involved converting the slip data to two categories, that is, "low" and "high", which correspond to $0-30\%$ and above 30%, respectively. Slope and thermal inertia were also categorized into different classes. Slope categories were taken from Ono et al. (2018), where the ranges considered are $0-5°$, $5-10°$, $10-15°$, $15-20°$, $20-15°$ and above $25°$. However, slope above $15°$ are



(a) MERB traverse (total length: 45.16 km) and slip checks.



(b) MERA traverse (total length: 7.751 km) and slip checks (the part where checks were performed is zoomed in).



(c) Legend

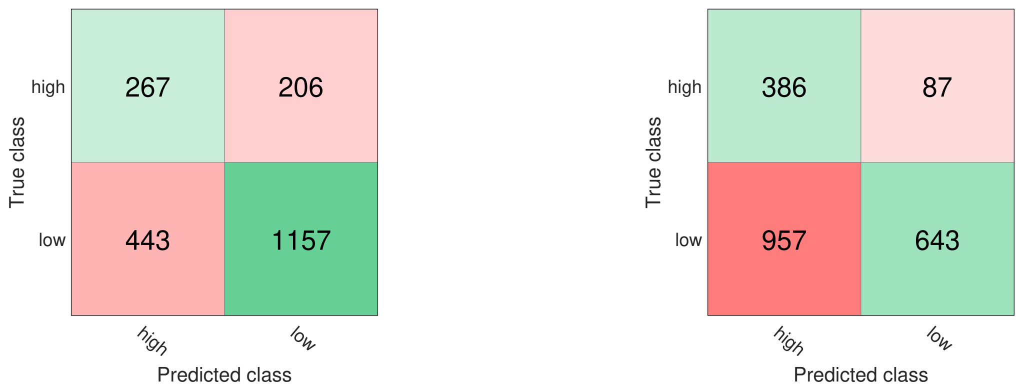
Fig. 2: *Data points available for this study. (a) Slip checks with orbital coverage available for Opportunity (in red, B data kept for validation). (b) Slip checks with orbital coverage available for Spirit (in red, A data used for training). (c) Legend.*

already considered complicated terrain (Biesiadecki et al., 2007), therefore only 3 categories of slope were considered: $0-10°$, $10-15°$ and above $15°$. Each category was then split to account for the direction of the slope, that is, up or down. Thermal inertia was also divided into categories, with high thermal inertia above 200 TIU and low thermal inertia below 200 TIU.

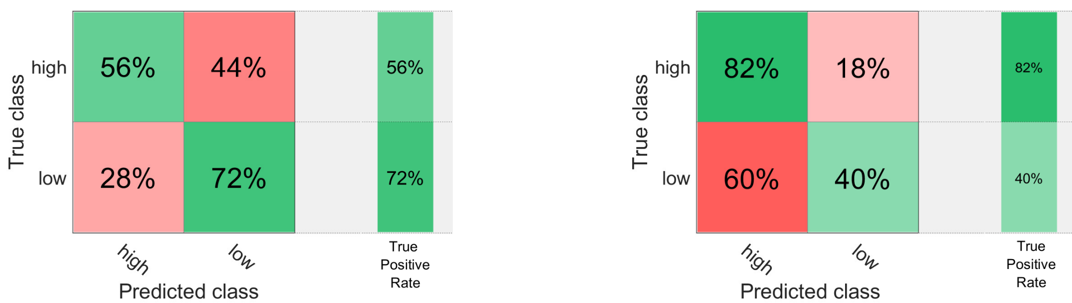
Multiple classification methods were considered, including: trees, naive Bayes or nearest neighbors. The Spirit data were used for training the classifier (referred to as the A set) and the data from Opportunity were used for validating the trained classifier (referred to as the B set). However, it should be noted that among the 2 categories, both for the training data and the testing data, the first category is over-represented. For all data sets combined, there is a total of 5323 slip check points with the required orbital coverage, with 4491 belonging to class "low" (84.4%) and only 832 belonging to class "high" (15.6%). Among the A set (from Spirit's traverse), 1600 are category "low" (77.2%) and 473 are "high" (22.8%). Among the B set (from Opportunity's traverse), 2891 are "low" (89%) and 354 are "high" (11%). This led to an imbalanced class problem for training the classifier that needed to be taken into account. There are ways to handle the class imbalance so that the model does not get biased towards the most represented category, including tuning the misclassification cost matrix or using boosting and/or sampling methods (Weiss, 2004) such as AdaBoost (Adaptive Boosting) (Liu et al., 2008) or RUS (Random Under Sampling). Authors have also proposed to combine both sampling and boosting methods to improve even further the performance of a classifier when handling imbalanced data, called RUSboost (Seiffert et al., 2008). When compared to different algorithms, RUSboost was proved to perform better than sampling or boosting methods alone (Seiffert et al., 2009).

5. Results

5.1. Classifier training



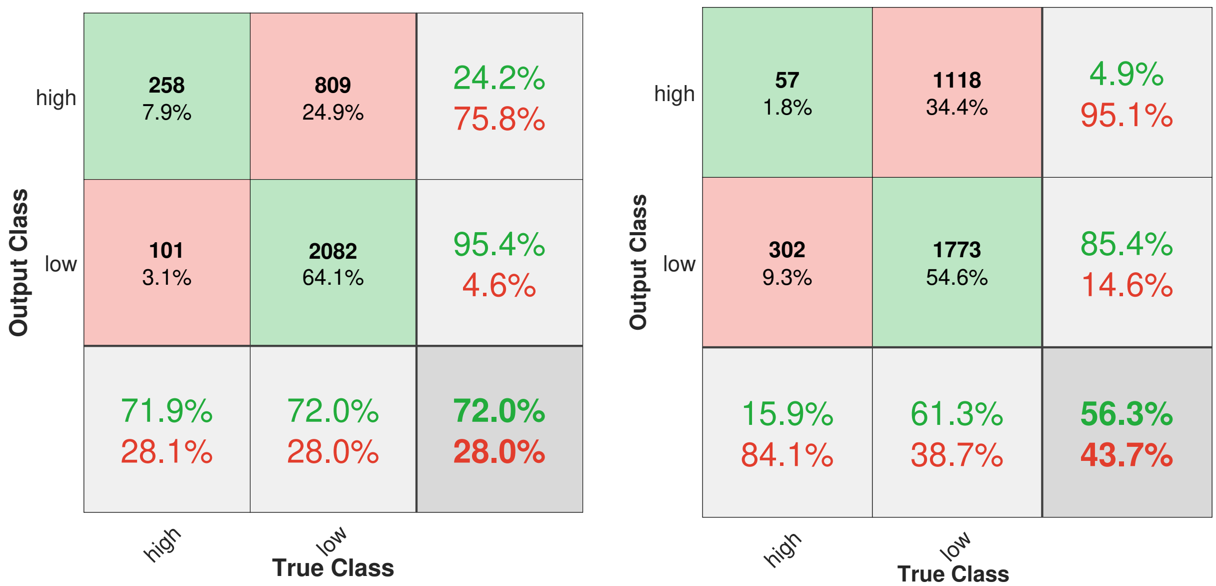
(a) *Number of observation (2 predictors)* ***(b)*** *Number of observations (1 predictor)*



(c) *True positive rate (2 predictors)* ***(d)*** *True positive rate (1 predictor)*

Fig. 3: *Confusion matrices showing the performance of the trained model on data set B2.*

As a result of the PCA analysis in section 4.1, the classifier was trained using the variables contributing the most to the explained variance, that is, slope and thermal inertia. The best results were obtained using a decision tree classifier with a RUSboost algorithm and a penalty cost of 5 for "low" misclassified as "high" and 1.5 for "high" misclassified as "low". The classifier algorithms was first chosen based on overall performance and has the following characteristics: maximum number of split is 50 and the number of learners is set to 30. The same model was then trained without thermal inertia as a predictor. The performance of the classifier is presented in Fig.3. The overall performance is 68.7% for the classifier with two predictors and drops to 49.6% when using only slope as a predictor. The overall performance the trained models tends to confirm the results from the PCA analysis, demonstrating the need for thermal inertia. Low slip prediction increases from 40% to 72% when adding thermal inertia; however, high slip prediction shows better results when the algorithm is trained with one predictor only. Overall, the conclusion is that thermal data are an important component of slip prediction analysis.



(a) *Results for test data using 2 predictors*

(b) *Results for test data using 1 predictor*

Fig. 4: *Confusion matrices on test data set B for (a) model with 2 predictors and (b) model with 1 predictor.*

5.2. Validation on new data

All data from the B set were used to test the trained classifier. The results are presented in Fig.4 where the algorithm using thermal inertia and slope as predictors (Fig.4a) and the model taking only slope as predictor (Fig.4b) are tested.

The results show that the overall performance of the model is good (72.0%) and decreases significantly (down to 56.3%) when using only slope as a predictor. This confirms that thermal inertia is an important value to consider when predicting slip. The model is capable of predicting low slip and high slip pretty well, scoring 71.9% and 72.0% of the data, respectively. When thermal inertia is dropped and slope only is used, the model goes barely above average for low slip data, predicting only 61.3%, and does not even correctly categorize more than a quarter of the high slip data, scoring only 15.9%. The model trained with only slope as predictor therefore performs poorly and these results reinforce previous conclusions: thermal inertia is a valuable asset to the prediction of mobility performance.

6. Conclusion

This work implemented a classifier that takes orbital data as input to predict whether slip will be greater or less than 30% over chosen areas. By comparing the same type of classifier with difference input, it is established that thermal inertia plays a key role in predicting the amount of slip the rover is likely to experience, as suggested in Cunningham (2017). Indeed, thermal inertia gives valuable insight into the first few centimeters of the terrain, which greatly affect the rover performance. When paired with slope, thermal inertia is able to predict with good accuracy the range of slip a vehicle will experience on a given terrain.

Future work includes studying the performance of this classifier at other landing sites, such as Gale Crater, and improving its efficiency with the additional information.

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