DEEP TERRAIN ESTIMATION FOR PLANETARY ROVERS

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ABSTRACT

This research is developed within the ADE (Autonomous DEcision making in Very Long Traverses) project funded by the European Union to develop novel technologies for future space robotics missions. ADE's objective is to increase the range of traveled distance of a planetary exploration rover up to 1 km/sol, while ensuring at the same time optimal scientific data return. In this context, the ability to sense and classify the type of traversed surface plays a critical role. The paper presents a terrain classifier that is based on the measurements of motion states and wheel forces and torques to predict characteristics relevant for locomotion using machine and deep learning algorithms.

The proposed approach is tested and demonstrated in the field using the SherpaTT rover, that uses an active suspension system to adapt to terrain unevenness.

1 INTRODUCTION

ADE [1] is an ongoing European H2020 research project, part of the PERASPERA second call [2]. Its ambition is to design, develop, and test in a representative Earth analogue a fully autonomous rover system. The ADE system is capable to take all decisions to pursue mission objectives, to increase data collection and overall science, to perform autonomous long traverse surface exploration, to guarantee fast reaction and adapt to unforeseen situations, increasing mission reliability, and guaranteeing optimal exploitation of resources. The description of the full ADE system is given in a companion ISAIRAS paper [3] to which the interested reader is invited to refer.

This paper details one of the key technologies to enable long range applications of planetary rovers related with terrain awareness. As a matter of fact, the mobility range capability of the rovers has been up to date strongly limited to few tens of meters per day [4], [5], [6]. From a purely technical point of view, this limitation is mostly due to the rover locomotion system and its power storage capabilities from one side, and the other by the lack/reduced skills in terms of autonomous capability to take decision on-board. The result is the impossibility to cover reasonable portions of/or multiples geographical areas of a potential planetary surface, reducing drastically the data returns both in terms of "pure science" and/or potential data collection for in-situ resources analysis and further exploitation. The importance of sensing hazards was highlighted in April 2005, when the Mars Exploration Rover Opportunity became embedded in a dune of loosely packed drift material [7]. The terrain geometry was not hazardous; however, the high compressibility of the loose drift material caused the wheels to sink deeply into the surface, and the combination of the drift's low internal friction and the motion resistance due to sinkage prevented the rover from producing sufficient thrust to travel up the slope. Opportunity's progress was delayed for more than a month while engineers worked to extricate it. A similar embedding event experienced by the Spirit rover in 2010 led to the end of its mobility operations [8].

Therefore, ADE's main objective is to design, develop and test key technologies suitable to overcome these limitations, performing long traverses while guaranteeing fast reaction, mission reliability and safety, and optimal exploitation of the robot's resources within reasonable costs. The envisaged idea presented in this paper is that terrain properties can be obtained by the rover's wheels that serve as tactile sensors. SherpaTT's wheels are outfitted with six axis load cells that provide a direct measurement of the forces and torques applied by the wheels to the ground and vice versa. In addition, estimation of the motion states in terms of accelerations and rate-of-turn can be gathered by an inertial measurement unit attached to the robot's body. All 20 joints of the suspension system provide telemetry including currents, voltages, PWM, temperatures, velocity, and position. Following this rationale, signals that are directly modulated by the terrain interaction can be obtained. These measurements represent a rich source of information that bring significant content in terms of terrain properties. The work presented in this paper applies learning approaches to this data in order to make intelligent autonomous robots adaptive to the site-specific environment [9], [10].

Figure 1: SherpaTT in soft sand dunes during Morocco field trials in 2018.

2 MATERIALS AND METHODS

The ground properties detection (GPD) system is tested and developed using the rover SherpaTT that is shown in Figure 1. SherpaTT was built by DFKI RIC for long-distance exploration applications [11], negotiation of highly challenging terrains or non-nominal conditions (sinkage in soft soil, getting entangled between rocks or alike), cooperation tasks between heterogeneous rovers in a collaborative sample return mission, search and rescue and/or security missions. SherpaTT is a four-wheeled mobile robot [12] outfitted with an actively articulated suspension system, independent drive and steer wheel motors and a six degrees of freedom (DOF) manipulation arm. Hence, the rover is a hybrid wheeled-leg rover, meaning it can take advantage of both, wheeled and legged locomotion according to the terrain difficulty. SherpaTT has a mass of about 180 kg and a payload capacity of at least 40 kg. Each of the four suspended legs has five DOF that include the rotation of the whole leg about the shoulder or pan axis with respect to the robot body, the two rotations of the inner and outer leg parallelograms for lifting a wheel, and the steer and drive angle of the wheel.

Each of the 20 suspension and six arm joints delivers telemetry data at a rate of 100 Hz. The telemetry includes joint position (absolute and incremental), speed, current, PWM duty cycle and two temperatures (housing and motor windings). Additionally, a 6-DOF force-torque sensor (FTS) is placed at the mounting flange of each wheel-drive actuator enabling the direct measurement of the generalized forces that each wheel exchanges with the supporting surface. Active force control for the wheel-ground contact as well as the roll-pitch adaption are two processes of the so-called Ground Adaption Process (GAP) in SherpaTT.

2.1 Data Set Generation

SherpaTT was remotely controlled to follow an approximately 10 m long straight path over three types of terrain: (i) unprepared sandy terrain, (ii) compact sand/gravel road, and (iii) paved ground. Sand and paved ground represent the two opposite extremes in a terrain classification scale, since sand can be regarded as a high deformable and low traction surface whereas a paved surface offers low/no deformability and high traction. For each terrain, five runs were repeated in forward drive and five tests in reverse drive. The speed of the rover was controlled as 0.1 m/s and 0.15 m/s. In Figure 2, the three different terrain types are shown taken during the experiments.

(a) unprepared sand

(b) compact sand/gravel road

(c) paved ground

Figure 2: SherpaTT during test runs

All runs were conducted with a fueled power generator mounted to SherpaTT. It can be seen as a red box at the back of the rover in Figure 2.

The generator is used for the long traverse in the project as a replacement for solar panels of a flight system, in order to guarantee a 6-8 hour long operational time. Note, that the generator's vibrations might be included in the body's IMU data. Reference runs on battery without vibrations from the generator were also conducted but are not considered yet for the results of this paper.

2.2 Learning approaches

Terrain classification represents a challenging task due to high variability in surface type and lighting conditions, possible lack of structure, and no prior information. In this context, heuristic or expert systems may perform poorly, whereas learning approaches may provide better performance [13], [14] [15], [16].

The general learning process includes gathering of data pertaining to the vehicle-terrain interaction followed by a mapping stage of data with the corresponding terrain. This functional relationship can help addressing various issues: (a) difficulty in creating a physics-based terrain model due to the large number of variables involved, (b) the mapping from proprioceptive input to a mechanical terrain property is an extremely complicated function, which does not have a known analytical form or a physical model and one possible way to observe it and learn about it is via training examples, (c) a learning approach promotes adaptability of the vehicle's behavior.

In this research, we use a deep neural network to solve the classification problem of different terrain types. Therefore, sensory signals are fed in the form of spectrograms to a Convolutional Neural Network (CNN), showing better performance when contrasted with standard Support Vector Machine (SVM).

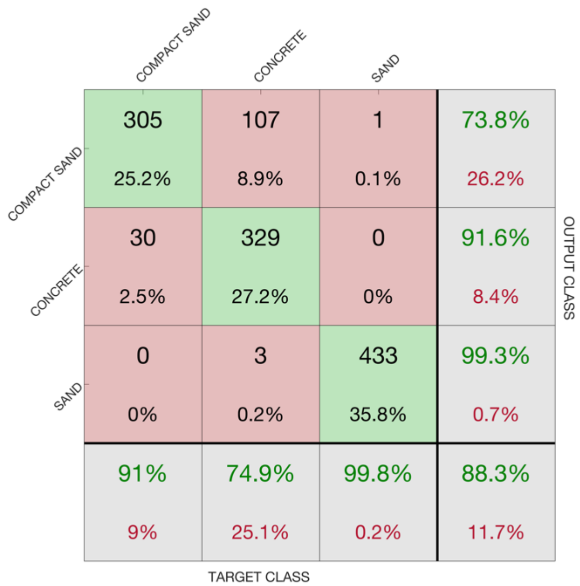
3 EXPERIMENTAL RESULTS

The deep CNN terrain classifier is validated in the field using real data gathered by SherpaTT operating on different surfaces. The motivation is double fold. On one hand, the discriminative power of proprioceptive signals (e.g., inertial and force measurements) is quantitively evaluated. In this respect, three different classifiers are built: two classifiers that are trained using each singular sensor modality, and one algorithm that combines both sensory data. On the other hand, the performance of a deep convolutional net is compared with SVM.

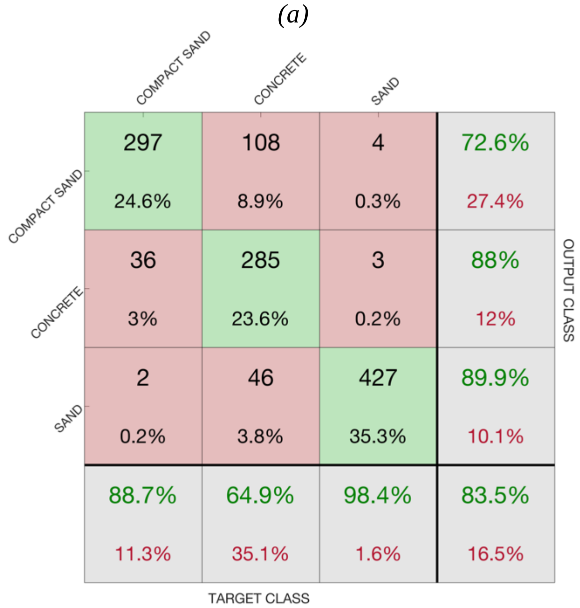
Raw data collected by SherpaTT with a sampling rate of 100 Hz during straight runs are partitioned in four folders, and, then, windowed in 1-second adjacent samples. The multimodal observation is then fed in the CNN classifier in the form of multichannel spectrogram, whereas first and second statistical moments are extracted for the SVM embodiment. 80% of the available windowed in each folder is used as training set, whereas the remaining 20% is left out as testing set.

Comparison between the two learning approaches is presented in terms of confusion matrices, as shown in Figure 3, Figure 4 and Figure 5. Figure 3 shows that an IMU data-based learning approach can give around 85% accuracy. The convolutional neural network, based on signals spectrograms in Figure 3(a) reaches 88.3% accuracy. Meanwhile SVM, exploiting mean and standard deviation in Figure 3(b) is 4.8% less accurate. Precision of models is also presented in the last column and sensitivity values are contained in the last row. Both models show consistent precision and sensitivity values with lower values on paved ground and compact sand, which are terrains with relatively high adherence compared to sand. Lower sensitivity value is relative to SVM capability of discerning concrete samples from sand ones, based only on IMU signals.

Figure 4 contains results of classification models based only on measurements of forces and torques exchanged between the rear left wheel and the ground. Both SVM and CNN models trained on signals provided by a single load-cell are quite as much accurate as the corresponding IMU-based ones. CNN performs 0.6% better while SVM is 2.3% less accurate. Variation of accuracy can be explained comparing the four confusion matrices and considering the increasing compact sand samples misclassified as sand ones, as showed by both CNN Figure 4*(a)* and SVM Figure 4*(b)*. Refer to row Sand and column Compact Sand (red element S-CS). This variation is balanced in Figure 4*(a)* by CNN model with the increasing correctly classified paved samples (green element C-C) previously mistaken in Figure 3*(a)* as compact sand (CS-C). SVM instead presents in Figure 3*(b)* a larger number of misclassified paved samples as Compact Sand (CS-C), thus explaining the reduction in accuracy. Relevant is also the comparison between *(a)* and *(b)* of Figure 4.



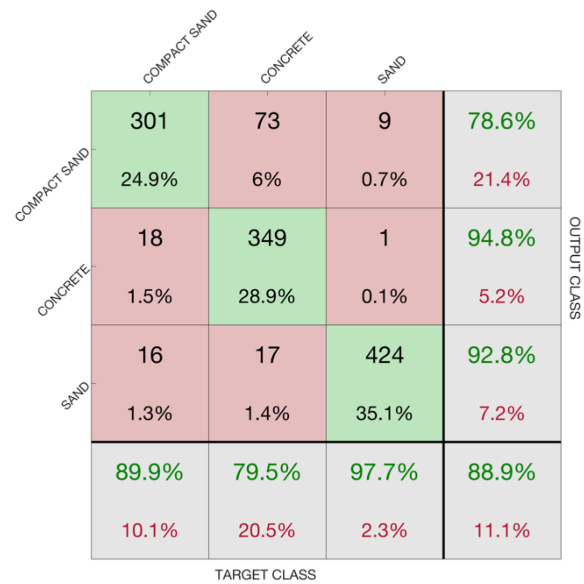
(a)



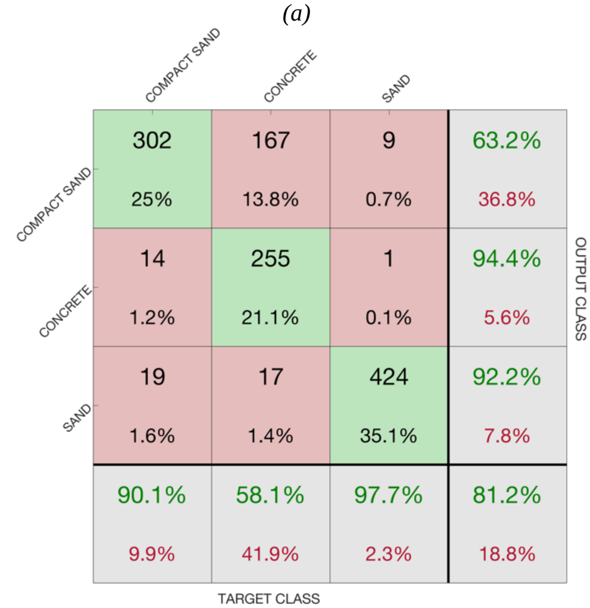
(b)

Figure 3*: Confusion matrices obtained from the CNN (a) and SVM (b) terrain classifier trained with IMU data*

The two confusion matrixes not only present about the same number of correctly classified Compact Sand samples (CS-CS), but also the same Sand sensitivity: 97.7%. Correspondence between Sand sensitivities of models indicates that the two are equally good at recognizing sand when driving on it. Moreover, correspondence of elements S-C and C-S of both *(a)* and *(b)* indicates that the two models are equally good at discerning Sand from Paved ground because they mistook the exact same number of paved ground samples for Sand and vice versa.



(a)

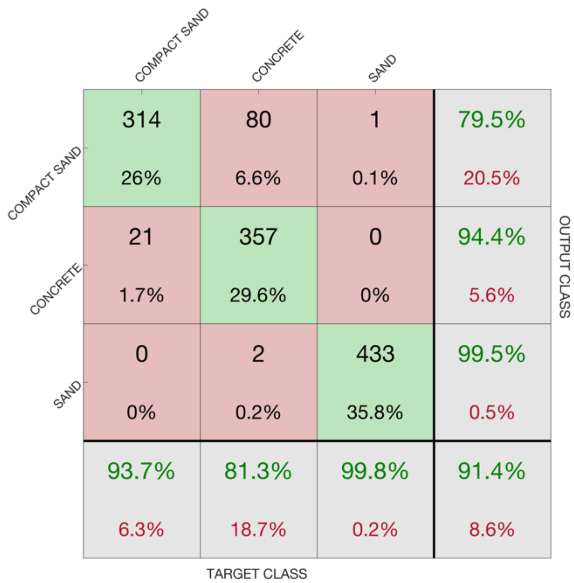


(b)

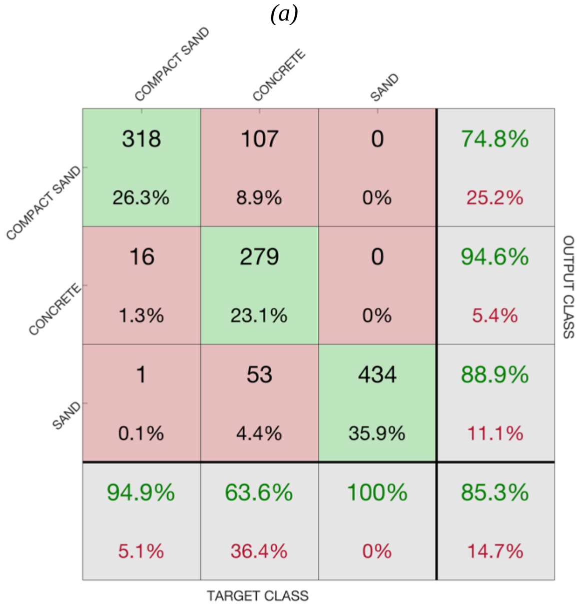
Figure 4: Confusion matrices obtained from the CNN (a) and SVM (b) terrain classifier trained with load-cell data.

Therefore, providing a wheel with a load-cell will give the rover about the same capacity of discerning between two opposite terrains in terms of traction as Sand and Concrete when using a model that relies only on force and torque data.

Figure 5 underlines the importance for a model to be able of fusing the information provided by different sensors.



(a)



(b)

Figure 5: *Confusion matrixes obtained from the CNN (a) and SVM (b) terrain classifier trained combining inertial and force signals.*

In this respect, the CNN model shows higher capability of fusing IMU and load-cell data to recognize terrain than SVM, reaching 91.4% of accuracy Figure 5*(a)* outperforming SVM of 6.1% Figure 5*(b)*. Using both IMU and load-cell data still results in higher SVM accuracy than using just one of the two sensors, but SVM does not gain from sensor fusion as much as CNN does. In fact, providing the IMU-based SVM with load-cell data results in a 1.3% more accurate model, whereas providing the load-cell based CNN with the IMU data produces a 2.5% more accurate neural network.

In order to summarize the results, Table 1 collects the performance metrics of the three classifiers analyzed.

Classifier type	Accuracy (%) SVM	CNN	Improvement (%)
IMU-based	83.5	88.3	5.7
Load cell-based	81.2	88.9	9.5
Combined	85.3	91.4	10.5

Table 1: Performance metrics obtained from the proposed terrain classifiers

Each single sensor modality appears to perform equally well. Inertial and force signals are comparable in terms of discriminative power for terrain classification (first and second rows). However, when combined they provide better classification performance (third row). As for the learning algorithm, CNN outperforms SVM for both the single-sensor modality and the combined implementation (compare the first and second columns). In the latter case, an improvement of more than 10% is found, as shown in the third column of Table 1.

4 CONCLUSIONS

The ADE project is designed and developed having a set of objectives in mind. Its main objective is to address the current challenges that planetary rover exploration has. ADE is a complex system-of-systems, in which each component is designed to fulfill a specific purpose for reaching the project's objectives.

Among the main capabilities provided by ADE is to enable long traverses. To this aim, terrain classification results in a critical component.

Data provided during straight forward run by SherpaTT's IMU and rear left wheel cell-load are for this purpose gathered and analyzed. A 4-fold cross-validation process is carried on among runs and two machine learning algorithms (SVM and CNN) are trained over 1 second long recordings corresponding to approximately 0.1 meters. Classification results are presented for the two models when based only on IMU data, only on load-cell data and with both sensory data. Analysis of corresponding confusion matrices show superiority of the deep-learning approach in classifying unfiltered data and fusing sensory information to provide a better estimate of the traversed terrain with respect to standard SVM-based machine learning classification.

Soil analysis capability will be demonstrated in a Mars analog scenario within the next months during the field tests. Similar tests will be conducted for the terrestrial use case.

Acknowledgement

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