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RTILE - Adaptive rover navigation based on online terrain learning

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Abstract

In the scope of this work, a framework, called Rover Terrain Interaction Learned from Experiments (RTILE), was developed to handle the uncertainties of the rover environment. This framework allows the rover to learn a Bayesian model associating the rover-terrain interaction (RTI) characteristics and the observation of the terrain at a distance. The same model can be used to predict the RTI characteristics and then, optimize the rover path accordingly. This paper focuses on this optimizing process. A direct trajectory to reach a goal can be challenged as long as it shows improvements in terms of rover-terrain interaction. This process has to take into account that the learning mechanism is unsupervised and therefore must be dynamically updated. The CRAB rover is used in this work for the implementation and testing of the approach.

1 Introduction

In order to move a valuable payload safely and reliably, a rover has to interact with its environment, which is by nature an unknown actor. Hence it seems interesting to design a framework allowing a rover to learn from its experience while it operates in a mission, the final goal being to use the accumulated knowledge to optimize the rover path. As the terrain is, at least partially, unknown and is extremely difficult to characterize beforehand, the rover has to rely on unsupervised technics to build its own representation of its interaction with the terrain.

1.1 State of the art

Several research works have been dedicated to allowing a rover to learn from its interaction with the terrain. [1] proposes to learn the slippage model of the rover with respect to the terrain type and geometrical characteristics. In [2] it is argued that an autonomous system, in addition to learning from training data, should be able to detect and classify new terrains. The authors propose a Gaussian mixture model for detection and classification of novel terrains. [3] proposes a classification method making use of both visual and vibration data, comparing several classification methods. It shows great results at classifying terrains encountered but fundamentally the process is a supervised one. Among those approaches, few attempt to anticipate the rover-terrain interaction. In [1], the terrain appearance is divided into well known classes providing a prior set of trained classifiers. The number and type of the terrain is then fixed and the slippage model is then learned for each one of those. In the case of [4], it is the other way around as the visual characteristics of the terrain are learned online while the rover-terrain characteristics classifiers are trained before hand. One way or another, those approaches rely on trained classifiers which implies a given and fix number of classes.

1.2 Objectives

To improve this interaction, we developed a framework called RTILE (Rover-Terrain Interaction Learned from Experiments) that provides the rover with the capability to link remote and local data. Sensors such as a camera, acquire data of the environment at a distance and this remote data is used to build the remote terrain perception (RTP) model. Local data expresses the rover-terrain interaction (RTI) model which can be related to proprioceptive sensors such as an IMU. Those models are learned online and this process occurs automatically, and is unsupervised in the sense that it requires no preliminary training, nor any inputs regarding the number of terrain classes to learn. On the other hand, the model can be used to predict the RTI characteristics of the terrain ahead of the rover. The rover path can then be optimized based on the characteristic rating the RTI, called RTI metric, \( M_{RTI} \). This paper focuses on the development subsequent to [6].

1.3 Content

The next section gives an overview of the RTILE framework, allowing a rover to learn an RTI and RTP model to optimize its path. Section 3 describes in more details the process of using the predicted RTI metric to optimize the rover path. The following section presents the rover as well as the test environment for the experiments described in Section 5. The tests described there highlights clearly the impact of the approach. The paper concludes with a summary of the present research and its possible future.
2 Approach Overview

The generic concept of RTILE is presented in Fig. 1. The near to far part performs the local and remote data associations using a grid-based approach. A Bayesian model [7] is used to handle the uncertainties and its various probability distributions are asserted in the learning part. The prediction makes use of the knowledge acquired to estimate the RTI ahead of the rover. Finally the path planning uses the predicted RTI to influence the rover trajectory. Note also that here, the focus is not on the traversability (where the robot is able to drive or not) but on a complementary aspect, namely to differentiate the areas traversable with respect to their terrainability (ability to negotiate terrain irregularities) [8].

2.1 Probabilistic Model

The idea is to express the connection between the RTI and the RTP characteristics. The RTI characteristics, computed with the data from the local sensors, are named $F_l$. The RTP ones are named $F_r$. Note also that $F_j$ and $F_l$ are not expressed directly with respect to each other but first clustered into classes, $K_l$ and $K_r$, respectively. The Bayesian model and its decomposed joint distribution is expressed as follow:

$$P(F_r, F_l, K_l, K_r) = P(K_r)P(K_l | K_r)P(F_l | K_l)P(F_r | K_r).$$

Finally, what interests us is to answer the question: What are the predicted $F_l$, based on the observed $F_r$?

Based on the Bayesian model, the following answer can be given:

$$P(F_l | F_r) = P(F_l | K_r = \tilde{k}_r),$$

with the most likely remote class $\tilde{k}_r$ defined as:

$$\tilde{k}_r = \arg\max_{k_r} (P(K_r | F_l))$$

Eq. 2 corresponds to assuming the classes are well separated in the features space, meaning that their probability distributions have to be peaked.

The various distributions of the joint decomposition are learned according to the rover experiment. Thus, the distributions of $F$, the variable associated with the features, with respect to $K$, associated to the class number, are based on Gaussian model. Furthermore as a grid based approach is used, the cell containing both RTI and RTP data provide knowledge about how probable the connections between the feature spaces are. It allows calculating and updating $P(K_r | K_l)$. Finally eq. 1 allows us to determine the most probable predicted local features $F_l$ based on the remote features $F_r$.

2.2 Path Planning

E* [10], a grid-based path planner is used to drive the rover and reach the goal. The rover and goal positions being known, a navigation function is computed for each cell, stating the path’s cost to reach the goal from this cell. The underlying technique is expressed within the continuous domain, which corresponds to a wavefront propagating from the goal toward the rover. The path to reach the goal can be found by using a gradient descent over the navigation function. The E* grid consists of cells $c_e$ and $r(c_e)$ is the difficulty or cost of this cell. This parameter corresponds intuitively to the wavefront speed of the navigation function. In our work the propagation cost is computed not only based on traversability, $T$, but integrates the predicted RTI. Thus, we have:

$$r(c_e)^{-1} = f(\Lambda, T).$$

$\Lambda$ depends on the evaluation of the RTI, called $M_{RTI}$, computed based on the local features. $T$ depends mainly on the geometry of the terrain and can be considered as a Boolean value.

$$\Lambda = h(M_{RTI}) \text{ with } \Lambda \in [0, 1]$$

$$T = \begin{cases} 1 & \text{if the cell is traversable} \\ 0 & \text{otherwise} \end{cases}$$

$\Lambda$ takes a high value for a terrain having a good rover interaction. For example, assuming that the rover faces two terrains (named white and gray), as depicted in Fig. 2. The rover, which position is marked by the cross, has to reach the goal on the right hand side. If the rover is able to identify that $\Lambda_{\text{white}} > \Lambda_{\text{gray}}$, then the resulting generated trace (dashed) provided by E* naturally avoids the gray terrain and is a result of a gradient descent performed on the navigation function (illustrated by the wavefront). In summary, E* offers a tradeoff between the movement cost and the path length and it provides a trace to be followed to reach the goal.

Figure 1. RTILE schematic.

Figure 2. Wavefront propagation with E* [11].
possible trajectories. Therefore, according to eq. 3:

\[ T = 1 \Rightarrow r(c_e)^{-1} = \Lambda, \quad (8) \]

and to simplify the writing we use \( \Lambda \) in the next parts of the text to express the propagation costs.

### 3.2 Cost Function

The first step is to establish the relation between \( \delta M_{RTI} \) and \( \Lambda \), in conformity to the requirement that follows. This relation has to be true whichever \( M_{RTI} \) is asserted, and consistently with the overall RTI model, or the number of terrains “known”. Let us consider three terrains, respectively named \( A \), \( B \) and \( C \). Knowing that their RTI metric is as follows:

\[ M_{RTI}^A < M_{RTI}^B < M_{RTI}^C, \quad (9) \]

their difference can be computed as:

\[ \delta M_{RTI}^A = M_{RTI}^C - M_{RTI}^A = \delta M_{RTI}^B + \delta M_{RTI}^C. \quad (10) \]

The \( E^* \) algorithm, using the LSM\(^1\) kernel, has the propagation costs of its cell defined as:

\[ r(c_e)^{-1} = \Lambda \in [0, 1], \quad (11) \]

where a value of 1 represents a cell with the fastest wavefront propagation (and the lowest propagation cost), and therefore the best RTI metric. Thus, in order to use the full scale available (eq. 11), we assign the terrain showing the best \( M_{RTI} \) a \( \Lambda \) value of 1. Assuming the RTI metric is rated according to “the smaller the better”, the terrain of reference is \( A \), which gives us:

\[ \Lambda_{ref}^A = 1, \]

\[ \Lambda_{ref}^B = N(\delta M_{RTI}^B)^{-1}, \quad (12) \]

\[ \Lambda_{ref}^C = N(\delta M_{RTI}^C)^{-1} = N(\delta M_{RTI}^B + \delta M_{RTI}^C)^{-1}. \]

In order to have the different terrains expressed consistently within \( E^* \), their propagation costs need to be expressed proportionally. Thus one can express:

\[ \Lambda_{ref}^C = \Lambda_{ref}^A \cdot \Lambda_{ref}^B \cdot \Lambda_{ref}^C = N(\delta M_{RTI}^B)^{-1} \]  \( \delta M_{RTI}^B + \delta M_{RTI}^C \)^{-1}, \quad (13)

and the equations above are solved by defining the propagation costs as:

\[ \Lambda_{ref}^C = C_\beta \cdot \frac{\delta M_{RTI}^C}{\delta M_{RTI}^B + \delta M_{RTI}^C} = R(M_{RTI}^B, M_{RTI}^C) = N(\delta M_{RTI}^B)^{-1}. \quad (14) \]

\( R \) is a function expressing the relative propagation cost of a terrain \( t \) with respect to a reference terrain \( ref \). The parameters \( C_\alpha \) and \( C_\beta \) still need to be defined and they allow us to control the tradeoff between the deviation from the default trajectory and the resulting improvement with respect to the RTI metric.

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\(^1\)This stands for Level Set Method and express the type of interpolation method used within \( E^* \). LSM is the best \( E^* \) kernel [11].
3.3 “Unknown” Propagation Cost

The computation of the propagation cost is almost complete, except for the cost of the areas that are not yet observed, or classified as “unknown”. As the corresponding $M_{RTI}$ is unknown, a rule must be defined that will greatly impact the rover behavior. Thus a very conservative rule could define the RTI characteristic as bad as the worst terrain encountered so far (worst case) and the opposite rule, considering the “unknown” terrains as preferable as the best known so far, would result in a very adventurous. In our case, the propagation cost of the “unknown” terrain is rated based on the mean value of the best and worst terrain known.

4 Setup

The CRAB rover is a robot with six motorized wheels and a passive suspension system. The suspension system is composed of two symmetrical structures such as depicted in Figure 4. Also note that the CRAB rover concept is described with details in [12]. The following sensors are primarily used in the context of this paper:

IMU An IMU, MT-9B from Xsens, is mounted on the body of the CRAB. It provides the absolute orientation (Euler angles, $\psi_i$ with i being $x,y$ or $z$) of the chassis.

Monocular Camera An HD webcam from Logitech (Quickcam Pro 9000) provides two megapixel images of what lies ahead of the robot within a 53° field of view.

4.1 Feature Spaces and Metrics

Two feature spaces are used. The first one corresponds to the RTI characteristics and uses the data provided by the IMU. It represents the vibrations of the rover chassis, corresponding to the soil Softness:

$$F_i^{softness} = (\|\ddot{\psi}_x\|, \|\ddot{\psi}_y\|),$$  \(15\)

with $\ddot{\psi}_i$, corresponds to the rover chassis angular acceleration along axis $i$. Note also that as it is a series of data, the mean value is simply computed over the sequence corresponding to the grid cell treated.

The second feature space corresponds to the RTP characteristics and uses the camera data. It is a color description which corresponds to the soil Appearance.

$$F_i^{appearance} = (\Delta RG, \Delta GB),$$  \(16\)

with

$$\Delta RG = \frac{R - G}{v},$$  \(17\)

$$\Delta GB = \frac{G - B}{v},$$  \(18\)

$$v = \max(R, G, B).$$  \(19\)

The divisor is named $v$ as it is exactly how the V value is defined in the HSV color space.

As the whole idea of optimizing the path of the rover requires to determine the criteria driving this optimization, and therefore, choosing the function rating the RTI, $M_{RTI}$. According to the test environment and in order to show the impact of the overall method, we chose to minimize the amount of vibration within the structure, thus defining:

$$M_{RTI} = \sqrt{F_i^{softness}_1^2 + F_i^{softness}_2^2}.$$  \(20\)

Also note that to express what happened during the test, it is necessary to define metrics summarizing the rover behavior. Thus, two metrics are defined here, one corresponding to the distance traveled and the other corresponding to the softness of the terrain:

$$M_{Dist} = \sum \sqrt{\Delta x^2 + \Delta y^2},$$  \(21\)

$$M_{Soft} = \sqrt{\|\ddot{\psi}_x\|^2 + \|\ddot{\psi}_y\|^2}.$$  \(22\)

4.2 Environment

The test environment for the experiments is depicted on Figure 5. Three terrains are primarily used:

Asphalt Normal street pavement, the hardest terrain.
Grass Football field, the softest terrain of all three.

Tartan Athletic running track with a red appearance.

Thus we have:

$$M_{\text{Grass RTI}} = 0.14, \quad M_{\text{Tartan RTI}} = 0.67, \quad M_{\text{Asphalt RTI}} = 0.67$$

with the $M_{RTI}$ rated according to “the smaller the better”.

### 4.3 Parameters

In the test presented in the next section, consistent and constant parameters were used. Thus, the camera horizon, or maximum distance where the RTP feature are acquired, is $5 \text{ m}$. The rover speed is set to $6 \text{ cm} \cdot \text{s}^{-1}$, even though this speed is reduced when the rover turns for example. When learning activity is required, it is triggered by the distance traveled and occurs every $6 \text{ m}$. Finally, the constants $C_a$ and $C_b$, corresponding to the rover aggressiveness are respectively set to 0.4 and 4. It corresponds to a prior of the user knowing the $\delta M_{RTI}$ between grass and asphalt and wanting the rover to reach the optimal terrain if it is observed.

### 5 Experiments

This section is dedicated to presenting the results highlighting the impact of the whole RTILE approach. Two scenarios are primarily presented in the following.

#### 5.1 Test: Facing an “Unknown” Terrain

The test is divided in three parts. The setups of part $b$ and $c$ are depicted on Figure 6(a) and Figure 7(a).

In the first part, named $a$, the rover is asked to reach a first waypoint $15 \text{ m}$ ahead, and then another $30 \text{ m}$ ahead of the starting position. Performing a straight, direct trajectory, the rover moves first on asphalt, and then on grass. This allows the rover to learn a reliable description of both terrains. This knowledge is then used as a prior for parts $b$ and $c$, where no more learning is performed.

In part $b$, the rover aims for a goal positioned $12 \text{ m}$ meters ahead and a straight trajectory would drive the rover on grass for half of the trajectory, and then on tartan. However, the terrain description learned in part $a$ is used as a prior and the idea is to start from the best known terrain and to head toward an unknown terrain, the tartan. The test is also repeated five times to have more reliable results.

In the last part, $c$, the rover heads toward the same goal as in part $b$. This time, a straight trajectory drives the rover on asphalt for half of the trajectory, and then on tartan. Again, the terrain description learned in part $a$ is used as a prior. Accordingly, the rover starts from the worst known terrain and heads toward an unknown area. Similarly, the test is repeated five times.

#### 5.1.1 Result

Part $a$ While moving on asphalt and then on grass, the rover has the opportunity to integrate those terrains both to its RTI and RTP models. The RTI metric of both terrains are the following:

$$M_{\text{Asphalt RTI}} = 0.67, \quad M_{\text{Grass RTI}} = 0.14$$

This corresponds to the prior used for part $b$ and $c$. 
Part b The rover starts on grass and heads toward tartan, which is unknown at this point. The knowledge acquired in part a leads to:

\[ M_{\text{Grass}}^{\text{RTI}} = M_{\text{RTI}}^{*}, \quad (26) \]
\[ M_{\text{unknown}}^{\text{RTI}} = 0.4. \quad (27) \]

The resulting trajectories can be observed in Figure 8(a). It can be seen that the rover tries to remain as long as possible on grass in order to avoid the “unknown” area. The navigation costs of the whole environment corresponding to the knowledge accumulated during the test can be seen in Figure 6(b). The lighter area corresponds to the better terrain, grass. Its upper border shows the limit between grass and tartan, whereas the lower one corresponds to the limit of the camera field of view. The propagation cost corresponding to the “unknown” area is analyzed in the summary of the test.

Part c The rover starts this time on asphalt and moves toward tartan, having the same consideration as above. The resulting trajectories can be observed in Figure 8(b). The rover tries to avoid asphalt and diligently reaches the “unknown” area. Similarly to part b, the E* navigation costs are shown in Figure 7(b). The darker area, close to the starting point, corresponds to the asphalt.

5.1.2 Summary

The following tendencies can be observed:

- The rover remains on the same terrain when it is the best known so far.
- The rover looks for a better terrain when on a “bad” terrain.

In fact the results of this experiment are qualitative. In parts b and c, the tartan represents an “unknown” area but its RTI metric could be better than the best known so far, or on the contrary, worse than the worst. Therefore, it is difficult to determine what the “right” trajectory is and any quantitative comparison with the default trajectory is meaningless.

5.2 Test: RTILE Complete Approach

The rover is asked to reach a series of waypoints which, in conjunction with the environment depicted in Figure 5, corresponds to an interesting trajectory with respect to RTILE. For the purpose of explaining the test progress, the notion of section of trajectory, is introduced here. Thus section i refers to the trajectory part between waypoints i − 1 and i.

Section 1 proposes the rover with a 13 m trajectory on tartan, followed by two meters on grass. The next section corresponds to a 15 m trajectory on grass and sections 3 and 4 present the rover with trajectories on asphalt, which are 15 m and 12.5 m long respectively. The different orientation of those four sections provides the trajectory with a square-like shape.

Section 5 and 6 are both 12.5 m long trajectories on asphalt, but they are positioned just beside other terrain types. The idea is to offer the rover an alternative, which can be exploited by RTILE. Therefore, section 5 and 6 have tartan and grass on the left hand-side on a default, straight trajectory linking the waypoints. Also note that the rover starts the test without any prior, therefore it makes only use of the RTI and RTP models learned during the test.

5.2.1 Result

The test was performed twice using the RTILE approach and twice to have a reference, or default trajectory. The resulting trajectories can be observed in Figure 9 and the result metrics computed for each section are presented in Figure 11.

Section 1 to 4 It can be observed that the rover used the first four sections to learn a description of the three terrains. In fact, the corresponding trajectories are not challenged with respect to the default trajectory, this is particularly true for section 1 and 2, where the RTILE trajectory superposes exactly with the default one. The RTILE trajectory of sections 3 and 4 show some variations which are a conjunction of two elements: The limited field of view of the camera and the bad RTI metric associated with asphalt, the worst terrain of the test. Once asphalt has been learned (Figure 9 area a), its corresponding RTI metric is worse than the one associated with the “unknown” terrain. The rover is surrounded by asphalt, but the areas out of the camera field of view are of class “unknown”. Hence the rover attempts to drive around the observed asphalt, resulting in the behaviors of those sections.

Section 5 to 6 In sections 5 and 6, the rover altered both times its default trajectory to profit from the better terrain on the left hand-side. According to the knowledge model learned, the terrains have the following RTI metrics:

\[ M_{\text{Tartan}}^{\text{RTI}} = 0.26, \quad (28) \]
\[ M_{\text{Grass}}^{\text{RTI}} = 0.11, \quad (29) \]
\[ M_{\text{Asphalt}}^{\text{RTI}} = 0.51. \quad (30) \]

Although both grass and tartan have lower RTI metrics than asphalt, the amplitude of the difference is different. This is observed in the behavior of the rover as well as the fact that the rover enters tartan (Figure 9 area b) less abruptly than grass (Figure 9 area c).

Finally, the different behavior between both RTILE runs at the beginning of section 5 (Figure 9 area d) can
be explained by the acquisition and processing of camera images, occurring at different times.

Despite the variation that can be observed between the RTILE trajectories, the corresponding metrics are very similar as the very low variation shows it in Figure 11.

5.2.2 Summary

The test presented here combines both the learning and the prediction aspects for three terrains being learned dynamically and it shows nice and expected results. The RTILE trajectory has a slightly longer length but the vibrations within the chassis are significantly reduced when possible (see Figure 11 sections 5 and 6).

Figure 9. RTILE and default trajectories.

![Figure 9](image)

Figure 10. E* propagation costs grids.

![Figure 10](image)

Figure 10 shows the E* wavefront propagation costs grid at different locations (depicted as “points of interest” in Figure 9) which correspond to different terrain representation as well. Thus the overall figure shows the propagation costs are automatically adapted.

- At the beginning, no prior exists and the costs are initialized at the lowest value (Figure 10(a)). The first terrain learned (i.e. tartan) does not affect this representation as no point of comparison exists at this time.

- The second terrain learned (i.e. grass) results in an update of the E* propagation costs. The best terrain “observed” (i.e. grass) sees its propagation cost unchanged and remain at the lowest value (lighter area in Figure 10(b)). The rest of the grid, corresponding to the area unobserved, has its propagation costs set according to a RTI metric averaging the “best” and “worst” terrain known.

- As the rover reaches the end of section 2, the grid has been continuously updated during the movement of the rover and a light brown band can be seen on Figure 10(c), showing the area where grass was observed.

- Finally, Figure 10(d) shows the propagation costs associated with section 6 at the very end of the test. The light brown area corresponds to grass, the blue area corresponds to asphalt whereas the rest corresponds to areas that were not observed during the test. Note that those costs were adjusted once more when asphalt, a new “worst” terrain was learned.

6 Conclusions

The terrains classes are learned according to the rover own representation, based on the features representing the local and remote characteristics. In this respect, the features used in the context of the experiments should be adapted for space application, but the unsupervised approach and cost adaptation methodology proposed is very valuable. More concretely, the knowledge acquired during the mission, and the corresponding terrain description models need to be handled consistently if the learning mechanism generates a new class, or if the parameters of the existing classes are updated. In order to successfully solve this issue, a function connecting the terrainability, \( \Lambda \), and the predicted RTI metric compared to a reference, \( \delta M_{RTI} \), is introduced:

\[
\Lambda = C_{\alpha} \delta M_{RTI}^{C_{\beta}},
\]

where \( C_{\alpha} \) and \( C_{\beta} \) define the “aggressiveness” of the rover to look for the best terrain. Thus RTILE allows a rover
Figure 11. RTILE (∗) and default (∗) results.

to learn and use the knowledge of an unlimited number of terrains which is very useful for planetary rovers.

At the moment, $C_p$ and $C_r$ are established by an initial guess from the user, but it would be extremely interesting to close the loop and allow the rover to learn those parameters as well. This requires to be able to rate globally the trajectory performed by the rover and in this regard, a metric such as the energy consumption could be used.

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References


