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Long-Term Exploration & Tours for Energy Constrained Robots with Online Proprioceptive Traversability Estimation

Steven Martin and Peter Corke

***Abstract*— This paper is concerned with how a localised and energy-constrained robot can maximise its time in the field by taking paths and tours that minimise its energy expenditure. A significant component of a robot's energy is expended on mobility and is a function of terrain traversability. We estimate traversability online from data sensed by the robot as it moves, and use this to generate maps, explore and ultimately converge on minimum energy tours of the environment. We provide results of detailed simulations and parameter studies that show the efficacy of this approach for a robot moving over terrain with unknown traversability as well as a number of a priori unknown hard obstacles. We also present preliminary experimental results to show the feasibility of this approach in natural terrain.**

I. Introduction

Mobile ground robots have the potential to perform many of the routine tasks currently undertaken by scientists studying the environment. Currently the cost of data collection is a significant factor that limits both the spatial and temporal resolution and extent of measurements. In order for robots to undertake such missions they must be able to maximise their time in the field and minimise the time spent recharging or refuelling.

A mobile outdoor robot expends the bulk of its limited energy on mobility and the rate of expenditure is a function of the terrain over which the robot is driving, for example the local slope and the terra-mechanical properties of the ground. The challenge in planning energy efficient routes is that the terrain characteristics are generally a priori unknown, particularly the terra-mechanical properties. This necessitates methods for estimating the terrain characteristics of the ground over which the robot is driving and also for exploration of the environment.

Much previous work has focused on mapping obstacles and efficiently planning, and replanning, optimal paths around them. This approach is very effective in indoor environments but outdoors in unstructured terrain, with a sufficiently capable robot, most locations can be traversed with the expenditure of sufficient energy. Therefore we need to do more than simply classify obstacles in a binary sense — we require a more continuous estimate of the cost of moving over a patch of terrain to improve the quality of planned paths. For example Howard and Seraji [1] consider two classes of obstacles: hard and soft hazards. Hard hazards

The authors are with the CyPhy Laboratory, School of Electrical Engineering and Computer Science, Queensland University of Technology, Australia. steven.martin@qut.edu.au, peter.corke@qut.edu.au

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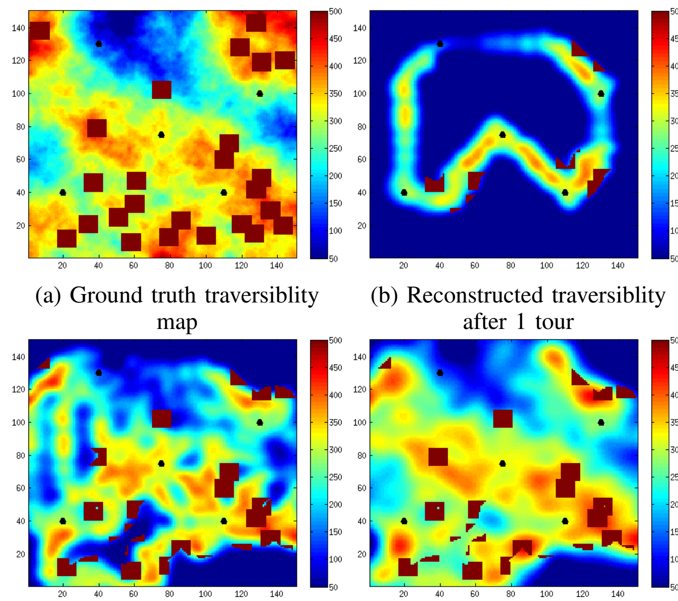

(a) Ground truth traversiblity map

(b) Reconstructed traversiblity after 1 tour

(c) Reconstructed traversiblity after 3 tours

(d) Reconstructed traversiblity after 5 tours

Fig. 1: The underlying traversiblity is reconstructed using a Gaussian Process regression from proprioceptive measurements. By the fifth tour the traversability is a good approximation of the ground truth. The terrain is coloured by instantaneous power usage (W) during traversal. The red regions indicate a priori unknown obstacles that are detected by a planar laser scanner.

are obstacles that can never be traversed, for example a wall. Methods for detecting and avoiding these obstacles is well covered by prior literature [2], [3], [4]. The second class is soft hazards, which are regions that the robot can drive over but at increased cost in terms of tractive power.

In this paper we propose a novel approach to this problem that we show is capable of energy efficient exploration and touring of environments with smooth or discontinuous traversilibity cost maps that are unknown a priori. We also consider that the environments contain a priori unknown hard obstacles or untraversable cells. Leveraging existing work on online traversability estimation we can build spatial maps of traversability, based on the robot's experience, which can be used for planning minimal-energy cost paths. Direct experience however is limited to the paths actually driven so we use Gaussian process (GP) regression to extrapolate traversability estimates, and we use this to determine prospective regions for exploration. Our vehicle energy model includes two components: mobility that is a function of terrain, and a constant

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(hotel load). The key contribution of this work is showing how explicit consideration of hotel load in combination with appropriate GP initialisation leads naturally to a simple and energy-efficient exploration strategy. Our motivating scenario is a robot performing repeated tours of a set of a priori known waypoints within a bounded region, and we provide extensive simulation results and statistics generated using Monte-Carlo techniques to show the efficacy of this scheme. The next section presents relevant prior work, and Section III describes our proposed technique for estimating the underlying terrain, exploring the terrain and planning tours. Section IV details the simulation environment and presents results and discussion of mapping traversability in natural and urban terrain. Section V presents some preliminary experimental results to demonstrate the efficacy of this approach on a robot platform in natural terrain. Finally, Section VI summarises our conclusions and discusses directions for future work.

II. Related Work

The cost of driving through a region is the traversability cost, or more in this paper simply traversability. This metric can be estimated directly from robot low-level sensor data or by classifying the type of terrain the vehicle is driving over into one of a number of known classes (eg. concrete, grass, gravel, etc) of a priori known traversability. In this section we provide an overview of current methods for estimating traversability and discuss why methods using proprioceptive sensing are beneficial for long term deployments.

A. Direct Traversability Metrics

The most common method of calculating traversability is to use the 3D structure of the surface. This can be gathered locally using common robotic sensors such as nodding or spinning LIDAR, stereo, structured light cameras or globally from aerial LIDAR.

A simple surface roughness-based traversability metric was used by Castelnovi et al. [5] to adapt the speed of mobile robot to the terrain immediately in front of it. In Molino et al.[6] several traversability metrics were developed that use roughness to determine the robot's ability to cross regions. Roughness has also been used by rover style robots, for example Singh et al. [7] used stereo vision to determine local roughness as well as terrain slope in order to plan paths that avoided rocky and sloped areas. The 3D surface structure can also be predicted from the configuration of the robot on the surface [8], [9] where the vehicle's stability or tractive force was equated to traversability. This approach is applicable to reconfigurable robots that can adapt their suspension or geometry to optimize the traversability in different regions [8].

B. Classification

Another approach has been to classify terrain. Robots often work in structured environments where the surfaces belong to one of a small number of classes with known properties. Once the class is identified its assumed properties can be used to inform a path planner.

Fig. 2: In many cases the traversability of terrain can be visually ambiguous. From left to right the loose gravel and exposed aggregate concrete, sand and concrete are both very similar in appearance however one has a high cost and one low cost in terms of traversability.

The primary sensor modality for classification has been imagery, for instance terrain color analysis [10], but this makes strong assumptions about the association between color and terrain and hence traversability. Learning techniques can be applied but the use of imagery usually requires some form of pixel-based terrain classification [11]. Attempts have also been made to link a priori information from satellite images with local classifications to improve long distance traversability estimates [12].

Classification is often simplified to a binary problem of whether terrain is locally traversable or not, leading to the well known occupancy grid world representation. This type of traversability classification has been demonstrated using a neural-network-based approach [13], [14], [15]. A binary classification is valuable for hazard avoidance but does not provide more nuanced information about the cost of moving across regions.

Classification of satellite and aerial LIDAR images into ground structure such as buildings, road and vegetation and then to a global traversability has been shown by Sofman et al. [16] and demonstrated on the Crusher platform [12].

A pure classification-based assessment has the disadvantages of relying completely on training data or expert knowledge of the traversability cost of each terrain class, and ignoring intra-class variation. The classification approach could be augmented to use proprioceptive sensors such as the wheel slip, vibration, energy consumption to infer whether or not the classification is successful and possibly to update the cost associated with the terrain class.

C. Self-supervised classification

A novel approach to self-supervised classification was demonstrated by Angelova et al. [17] that used onboard stereo imagery to determine a local traversability map and used estimated vehicle slip to supervise learning of the terrain classification. The work of Bagnell et al.[18] extends Silver et al. [12] to include online learning of the association between local traversability from onboard sensors and the classification of terrain from satellite imagery. A similar approach was applied to a lunar rover platform by Brooks et al. [19]. By using additional sensors to provide a better connection to the experienced terrain self-supervised learning is able to perform better classification and reduce the reliance on training and expert knowledge.

D. Proprioceptive sensing

The techniques summarised above have individual weaknesses. Sensors such as 3D laser for roughness estimation are expensive, bulky, heavy and power hungry that can be problematic for small, low cost and long endurance robots. Assumptions that rely on a strong a priori correlation between sensor measurements and terrain cost can be problematic, for example Figure 2 shows some cases where this assumption is invalid.

Proprioceptive sensors, which directly reflect the robot's experience of the terrain, avoid the assumptions and inference required for the approaches above. In prior work [20] proprioceptive sensors such as wheel slip, vehicle orientation, vibration and power consumption were used to map instantaneous traversability and a GP was used to estimate global traversability based on sparse sampling of locations selected by a random exploration. In this paper we use a similar technique and leverage the underlying properties of GPs to explore and map terrain while visiting waypoints within a region.

III. Technical Approach

Our problem is defined as visiting a set of desired waypoints, a tour, as often as possible given finite onboard energy — this requires us to minimize the energy used per tour. The traversability of the terrain is unknown in advance and the terrain also contains a number of untraversable obstacles that are unknown in advance. The robot must incrementally learn the relationship between location and motive power usage, and find an optimal path for visiting the goals. Assumptions made include: the robot is always localised; the waypoints can be visited in any order; the robot has sufficient sensors to measure local traversability online (eg. as described by Martin et al. [20]); the robot is equipped with a sensor that can detect untraversable obstacles (eg. a scanning laser).

Formally we express our problem as finding the path $\mathbf{x}$ that minimises the total energy consumption, E_t, for the tour

$$\mathbf{x}^* = \arg\min_{\mathbf{x}} E_t$$

subject to visiting a set of N waypoints $\mathbf{X}_w = \mathbf{x}_1, \mathbf{x}_2 \cdots \mathbf{x}_N$ so that $\mathbf{X}_w \in \mathbf{x}(t)$, $0 \leq t \leq T$. The energy consumed has two terms: motive energy that is a function of the path, the velocity profile, slope and traversability; and the hotel load that is the continuous power consumption of onboard computers, sensors and communications gear. The total energy is therefore

$$E_t = \int_0^T \left\{ P_m\left(v(\mathbf{x}(t)), \theta(\mathbf{x}(t)), \tau(\mathbf{x}(t)\right) + P_h \right\} dt$$

where $t \in \mathbb{R}$, $0 \leq t \leq T$ is time along the path, $\mathbf{x}(t) \in \mathbb{R}^2$ is the coordinate of the point along the trajectory; $v(\mathbf{x}) \in \mathbb{R}$ is the instantaneous velocity of the robot; $\theta(\mathbf{x}) \in \mathbb{R}^3, |\theta| = 1$ is a unit vector normal to the surface, ie. slope; $\tau(\mathbf{x}) \in \mathbb{R}$ is the local traversability metric; $P_m(\cdot) \in \mathbb{R}$ is motive power; $P_h \in \mathbb{R}$ is the hotel load power, and T is the total tour time.

In this paper we further assume that the terrain is flat and that the robot is moving at constant velocity (regardless of terrain) which simplifies the mobility energy term to $E_m\left(\tau(\mathbf{x}(t)\right)$.

A. Gaussian Process Regression

As the robot traverses the region it gathers samples of motive power usage. We utilize GPs to integrate the sparse samples at locations along the path into an estimated global cost map that can be used for planning. We use a homoscedastic regression with a squared exponential kernel

$$k\left(\mathbf{x}, \mathbf{x}'\right) = \sigma_f \exp\left(-\frac{1}{2l}\left|\mathbf{x} - \mathbf{x}'\right|^2\right) \quad (1)$$

where k describes the relationship between observations at $\mathbf{x}$ and $\mathbf{x}'$, and where σ_f and l are learnt hyper-parameters of the GP. The GP is assumed to have a zero mean that is equivalent to assuming that in the presence of no information the estimate will approach zero. We will exploit this assumption to bias the path planning algorithm towards exploration.

The squared exponential kernel is also called the Gaussian kernel and in practise has the effect of smoothing the data with a correlation proportional to distance. This is useful for natural environments that we assume are smooth but it does not handle discontinuous or rapidly changed scenarios well and can produce oversmoothed data [21].

In the scenario considered in this paper all training points, power measurements, will be positive but the regression could potentially estimate a negative cost in regions of high variance. This is unrealistic (perhaps possible with downhill regenerative braking) and also problematic for planning, so we clamp any negative motive costs from the regression to zero for planning.

In order to compare the known terrain model and the GP estimate, we sample both on a regularly-spaced grid and calculate the probabilistic log likelihood

$$PLL = -\frac{1}{2n}\sum_{j=1}^{n} \log 2\pi\sigma_j^2 + \frac{\left(\tau_j - \tau_j'\right)^2}{\sigma_j^2} \quad (2)$$

where n is the number of sampled points from the GP and τ is the true traversability value and τ' is the estimated traversability with variance σ. This measure accounts for the variance and gives a succinct indication of how well the GP predicts the entire distribution.

The computational complexity of Gaussian processes typically scales as $O(n^3)$ [22]. Despite approximations that can improve upon this the unbounded increase in the number of data points gathered during long term operations will eventually make recomputing the costmaps with GPs intractable. Therefore we bin the data points into terrain cells similar to the method proposed by Plonski et al. [23] that constrains the upper computational bound of the GP to being proportional to the number of cells in the terrain map rather than the robot's run time.

B. Path Planning

We use the D* algorithm [24] that allows distance costmaps to be precomputed before traversal and updated online if obstacles are encountered. The D* distance cost maps are also updated at the end of a tour when new traversability information becomes available.

The D* cost maps are used to estimate the cost of travel between all pairs of waypoints from that we solve the travelling salesman problem [25] to determine the best order to visit the waypoints. An exact solution to the travelling salesman problem was computed here that is reasonable given a low number (less than 50) waypoints and the computation can be performed at the base station rather than onboard the robot. For a high number of waypoints approximate solutions, such as those in Russel & Norvig [26] could be used.

IV. SIMULATION

In order to evaluate the effectiveness of this approach we simulated an area of synthetic "natural" terrain. The terrain was generated using a fractal pattern with motive power requirement varying from $P_{m_{\min}}$ to $P_{m_{\max}}$ and an average value of $\bar{P}_m$, and a fractal roughness parameter β. Non-fractal environments are considered in Section IV-C.

The patch of terrain has dimensions of 150 by 150 m. We also randomly place n hard obstacles, sized O_x by O_y, within the environment. The robot has a simulated hotel load of P_h, records its instantaneous motive power usage at 10 Hz, and the simulated planar laser scanner for obstacle detection has a range of 10 m.

Simulation Parameters	
n	25
O_x	10 m
O_y	10 m
P_h	50 W
$\bar{P}_m$	250 W
$P_{m_{\min}}$	0 W
$P_{m_{\max}}$	500 W
β	0.8

TABLE I: Baseline Parameters for Simulation

A. Simulated Monitoring Task

Using this detailed simulated environment we evaluated the system performance for a monitoring task: the robot was deployed on a tour to visit four locations and then return to base.

At the base, motive power information gathered during the tour was used to generate a new estimate of the traversability map using the GP regression. D* distance maps for each waypoint were updated with the new cell traversability. The cost and path to travel between each pair of waypoints was computed and the travelling salesman problem resolved to determine the best order to visit the waypoints given current terrain knowledge.

The robot used the precomputed path information to execute its next tour and the process was repeated until the robot finished 25 tours or the energy cost E_t converged to a constant. For all examined scenarios E_t converged within 15 tours.

This simulation was repeated 100 times in order to provide a statistically significant analysis of the performance of this algorithm. The location of obstacles and underlying terrain was varied for each simulation, with the location of the waypoints held constant. A summary of the parameters used in this simulation can be seen in Table I and Figure 3 shows a summary of a typical simulation example. An example of the evolution of the terrain map is shown in Figure 1.

B. Results

On its first tour the robot takes the shortest distance path since the estimated traversability is zero everywhere (the GP's initial condition), and the hotel load term, a constant energy burn rate, turns this into a minimum distance problem. On subsequent tours the traversability of previously visited cells is known whereas for unvisited cells the assumed traversability is initially optimistically low. The lower bound of the tour energy cost is the hotel load of the robot over the tour time, drawing the robot into those unexplored regions.

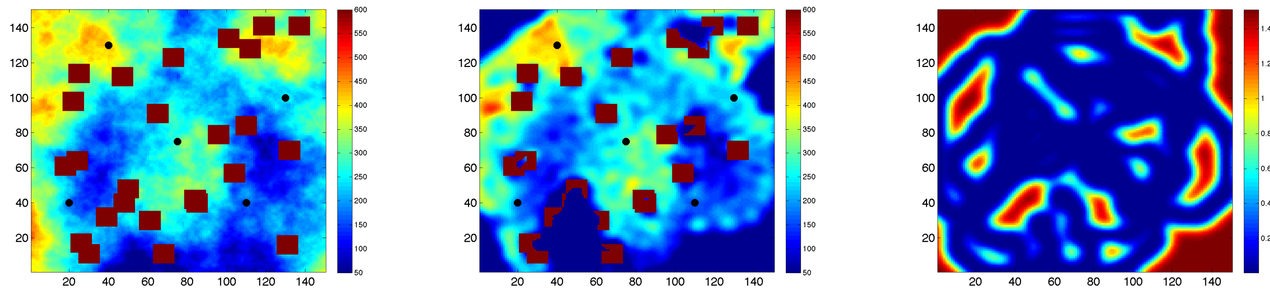
The robot will therefore explore different routes until converging to some (locally) optimal path. The estimated traversability map converges towards the true map after several exploratory tours, see Figure 5, but will never reach it as some areas are never explored. Terrain is optimistically assumed to have low traversability but areas will not be explored if the cost due to hotel load and the estimated travel cost will not provide a reduced energy cost.

We see this behaviour reflected in Figure 3e where there is an initial increase in the path cost as the robot explores, but as the map used for planning converges to a sufficiently good estimate of the terrain we see that the cost falls below that of the initial shortest distance path. The cost falls close to the minimal possible energy cost (computed using full knowledge of the ground truth traversability map and obstacles) — using exploration and online estimation the robot has found the energy optimal path.

98 out of 100 simulation runs showed improved performance when compared with the initial shortest distance path and the performance over all 100 scenarios improved by 15.4% on average. Of the scenarios that improved the average time to recoup the additional cost of the exploration was 8.8 tours. This is summarized in Figure 4 that shows a box and whisker plot of the energy cost to perform a traversal when compared with the known optimal tour cost. We can see there is a strong tendency to converge towards the optimal path energy cost. On average the cost of the converged path when compared to the optimal path was only 1.5% greater, with the worst case scenario being 12.5% greater.

The two cases that *did not* show improvement over the initial path occurred when the initial, shortest distance path, was coincidently also the minimum energy path. However the algorithm did return to the optimal path, but the energy wasted on exploration could never be recouped.

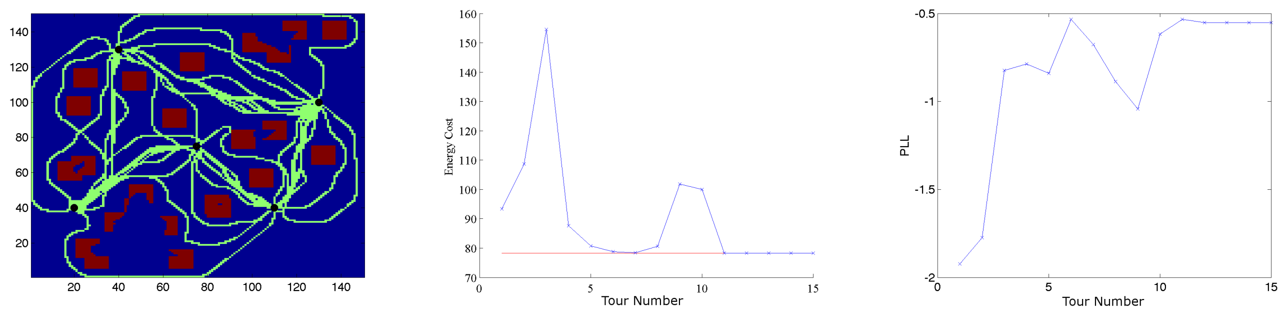
The hotel load is a realistic element of the robot's energy model but we have shown that it plays a key role in determining the robot's enthusiasm for exploration, which is, how far it will travel in the search for a lower cost path. For example, when the hotel load is high relative to the average



(a) Underlying fractal terrain model

(b) Reconstructed map

(c) Map confidence



(d) Explored paths and obstacles.

(e) Tour energy cost E_t vs tour number. The energy cost of the optimal path (given full knowledge) is shown in red.

(f) Map PLL vs tour number

Fig. 3: Simulated exploration in natural terrain after 15 tours.

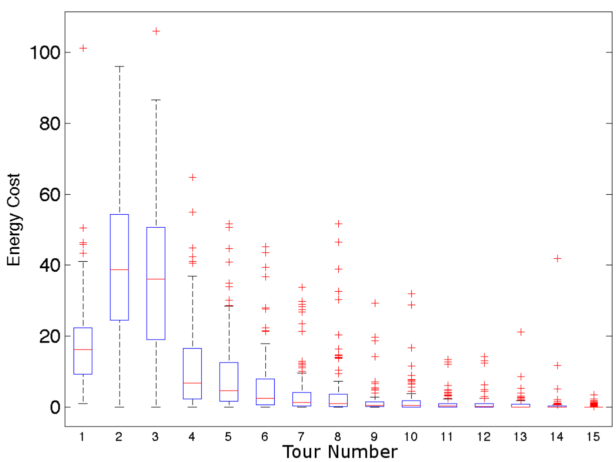


Fig. 4: Energy cost relative to the optimal path vs number of tours.

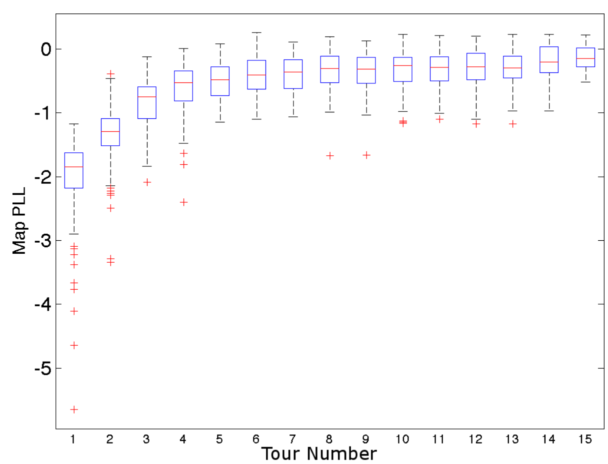


Fig. 5: Probablistic log likelihood vs tour number for 100 simulated scenarios, more positive indicates better fit to model.

traversability cost, any deviation from the shortest-distance path will incur a high energy cost due to the extra travel time. We see this clearly in Figure 6 where the simulation was run for the same underlying terrain while only the hotel load was varied — there is a marked reduction in exploration as the hotel load increases.

The reduction in exploration implies that there is a reduced benefit to exploration for robots with a high hotel load. To explore this behaviour further, as well as to discover corner cases and failure modes we conducted a sweep of parameters that we expected to influence performance and navigation behaviour. The first parameter was the terrain roughness, β, which controls how far the robot needs to travel in

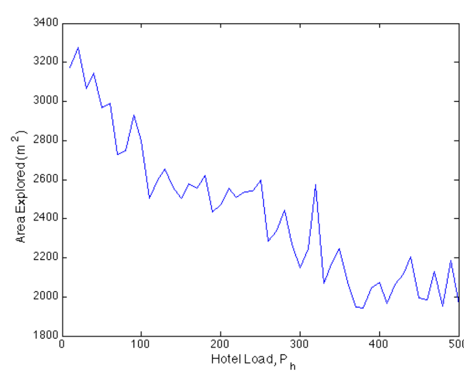


Fig. 6: Area explored vs hotel load.

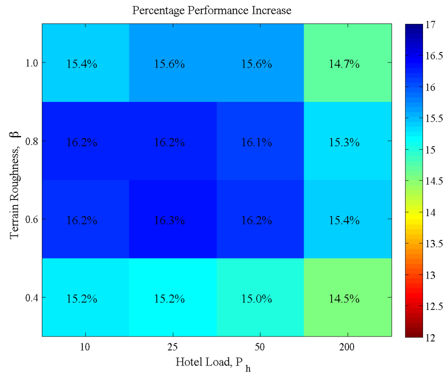


TABLE II: The average reduction in tour cost with varying parameters.

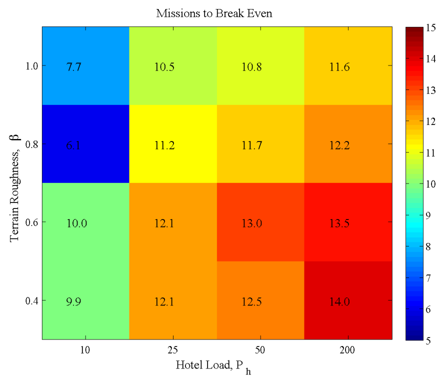


TABLE III: The average number of tours required to break even with varying parameters.

order to encounter a certain level of change in traversability. The second was hotel load, P_h, which as described above influences the robot's enthusiasm for exploration.

For each set of parameters we perform 100 simulations of the same terrain environments and the results are summarised in Table II and Table III.

Table II shows the average reduction in tour cost of the final tour cost relative to the initial tour cost. The improvement was approximately 15% for the entire sweep, and did not show any strong trend when varying roughness or hotel load — a relatively constant opportunity for improvement. For high roughness and low hotel loads there is slightly greater scope for exploration reducing energy cost since excursions have lower energy penalty and a greater likelihood of finding regions with lower traversability cost.

Table III shows the average number of tours until energy break even. We see that high roughness and low hotel loads scenarios require fewer tours than low roughness and high hotel loads scenarios.

Based on these results the time for that a robot is operating in a region is more important than the traversability cost. If required number of tours is high and there is variation within the terrain it is worthwhile to explore.

C. Urban Terrain

In the previous sections we examined the performance of our novel sensing and planning strategy for simulated natural terrain. However robots often need to operate in urban areas where the terrain is discrete and not described well by the fractal statistics we used for the natural environment, nor well describe by the squared exponential kernel. Here we present some initial investigations into applying our algorithm as is to a simulated urban environment constructed as shown in Figure 7a. The obstacles (buildings) are shown in red with low cost paths (roads) linking them in blue, between these regions there is sections of varying terrain cost (grass, gravel, gardens, etc.) that are coloured accordingly. These sections all had constant values and crisp boundaries.

Despite the world being poorly described by the kernel the exploration strategy was again able to converge to an optimal plan. A summary of this experiment is shown in Figure 7 and shows the exploration approximately reconstructs the underlying costmap. In this single case the exploration increased performance by 30% and anecdotally it shows that this approach could be applied to urban environments.

V. Experimental Results

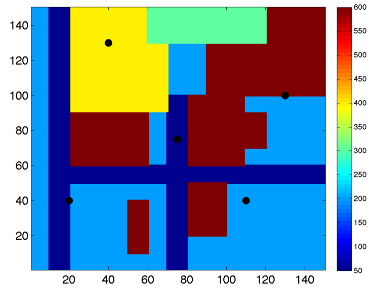
To validate the feasibility of the simulated approach some preliminary experiments were conducted. In this section we examine generating a map from proprioceptive sensors, in this case current sensors, and if there is sufficient variation in traversability to warrant exploration. Figure 8a shows the test platform, a Clearpath Robotics Husky rover. The robot is fitted with current sensors on drive motors and sensor/processing payload and it is localised using GPS fused with IMU and odometry using a particle filter.

For this experiment the robot was driven at constant velocity, we assumed the terrain was flat and did not model the affects of skid steering on power usage. Throughout the tests the average current consumed by the onboard computer and sensors was 1.5A and the drive motors approximately 8A, this is a comparable the the hotel load in the simulated scenarios.

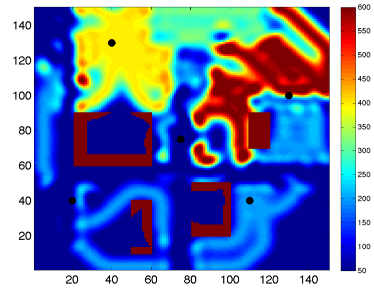
The experiment was conducted on a beach as it offered a location with predictable terrain variation and was approximately flat. As the distance from the water increases the sand is drier, softer and more difficult to traverse. To map the traversability, the experimental platform trawled a region, see figure 8b, at different distances from the water. This information was then used with the same GP regression to generate a traversability map.

Figure 8c shows the resulting traversability map from this experiment, it shows current varies from approximately 7A near the waterline up to 10A higher on the beach. We acknowledge this may be problematic as it biases the robot to drive towards water however this experiment focuses on demonstrating the feasibility of this approach on natural terrain whether this be grassland, desert, beach, etc. not avoiding water hazards.

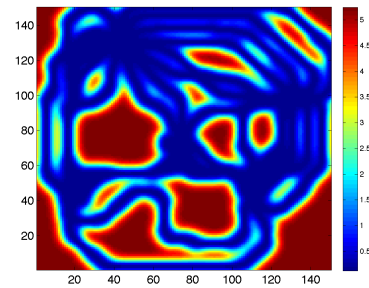
The second experiment was to test if there is sufficient variation in terrain in order to warrant exploration. Three candidate paths were chosen as shown in figure 8d between two points in the mapped area. Path A was the shortest distance path (black) and paths B and C were two exploration paths



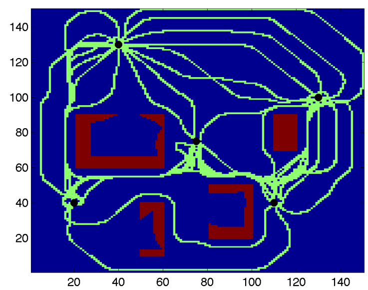
(a) Underlying discontinuous terrain model



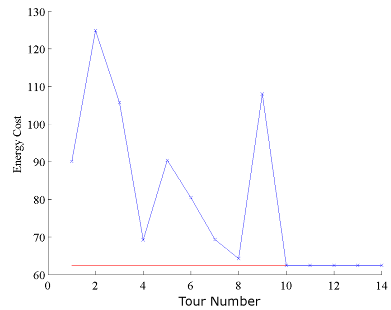
(b) Reconstructed map



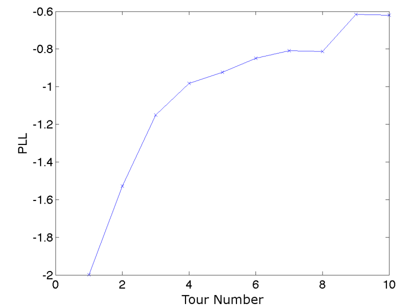
(c) Map confidence



(d) Explored paths and obstacles.



(e) Robot cost vs tours

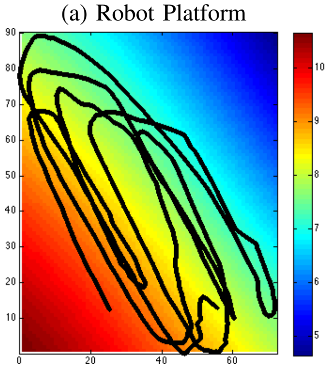


(f) Map PLL vs tours

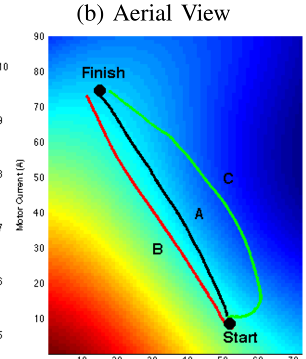
Fig. 7: Simulated exploration in urban terrain after 15 tours.

(a) Robot Platform

(b) Aerial View



(c) Reconstructed map



(d) Experiment Paths

Fig. 8: Traversability Mapping Experiment

one further from the waterline (red) and one closer (green) to examine if driving a longer path could be beneficial.

Table IV summarise the results from this experiment. The average motor current usage, C_M, shows that the regions further from the water were more difficult to traverse. The path times, t_p, for A & B were similar while path C was

	Path A	Path B	Path C
C_M	8.7A	8.9A	7.3A
t_p	118s	116s	133s
E_M	2480J	2500J	2340J
$E_H + E_M$	2900J	2920J	2820J

TABLE IV: Path traversal results.

longer. Despite this the total motor energy, E_M used in the longest path C was still lower than paths A or B. However once the hotel load, E_H, was accounted for the performance gained by taking the longer path was small.

This experiment demonstrates it is possible to reconstruct the terrain and that there is potential benefits for taking longer more traversable paths. This is a simple test with significant assumptions but we believe it demonstrates that this approach is feasible and warrants future work.

VI. Conclusion

We have described a system that can explore a terrain with a priori unknown traversability and obstacles and achieve a minimum energy tour of a set of waypoints. Online estimation of local traversability, from motive power, is used to update a GP regression of a global cost map that is used for planning optimal tours. We demonstrated the performance of the algorithm through detailed simulation and evaluated the potential for improved performance when compared with naive obstacle avoidance. We also considered how variation in the terrain may affect performance and when it is advantageous to explore. Our vehicle energy model includes a term for hotel load that we have shown is an implicit control on exploration: a high value penalizes exploration and tends toward minimum distance paths.

The exploration strategy was able to reduce energy cost relative to the first tour in 98% of the simulated scenarios. We have also demonstrated that the paths converge to an approximately optimal value and that for a long term operation the exploration cost can be recovered in relatively few tours. A very small number of cases were encountered in which the initial path was also the optimal path but the algorithm returned to optimal path but the exploration cost was never recouped — this is always the risk with exploration.

When considering a sweep of important parameters the simulation showed that, on average tour, the energy cost is reduced for all scenarios. It also highlighted that scenarios where the terrain has highly varying traversability costs and where the robot has a low hotel loads will benefit the most from exploration. Overall the simulation indicated that the time spent in a scenario, the number of tours, may be the dominant factor in determining whether exploration is beneficial from an energy perspective.

We believe these results make a strong argument for the use of exploration in long term deployments. Implementing this type of exploration requires minimal computation onboard the robot and the required proprioception can be achieved using very common robotic sensors. Utilising robot experience avoids the problems associated with misclassification of terrain and could be applied in variety of environments and scenarios.

A. Future Work

Our next step is deploying the system in a long term experiment and observing how the performance is improved in a variety of environments including the urban terrain. To achieve this practical extensions need to be made to relax the constraints used in this work, particularly flat terrain and constant velocity motion. We also need to consider the energy cost of turning that is not insignificant for a skid-steered vehicle.

The current planning and exploration strategy does not use the variance information from the GP and incorrect estimates in high variance areas may never be corrected. Incorporating this confidence into planning may increase the fidelity of the reconstructed costmap and avoid potential local minima. We also are interested in better understanding how the system copes with sudden or gradual changes in the environment, such as those due to weather, obstacles coming and going and changing waypoints.

Finally investigations into how traversability information can be incorporated into a traversability map online are planned with an emphasis on whether this shorter term adaptation shows significant improvement over the batch approach presented here.

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