Long Term Optimisation of a Mobile Robot with Proprioceptive Perception

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Abstract

Robots expended a significant portion of their energy on mobility therefore it is important to optimise paths for the terrain. Our previous work has demonstrated this optimisation in simulation and this paper is concerned experimental validation using a small scale robot. An energy-constrained robot can maximise its time in the field by taking paths that minimise its energy expenditure. We have shown that by recording motor power usage this can be used to generate maps, explore and ultimately converge to minimum energy tours of the environment. The comparison of simulated and experimental results on small scale robot shows equivalent convergence to optimal paths demonstrating the validity of the simulation.

1 Introduction

Mobile robots are well suited to repeated tasks such as data sampling or delivery of goods. These activities are still commonly undertaken by people and this is costly for both industry and research. The cost of data collection is significant and performing these tasks with robots can provide increased spatial and temporal resolution. In order to achieve these increases robots need to move efficiently and must minimise their time spent recharging or refuelling.

For a mobile robot the majority of energy is expended on mobility. The rate of expenditure is a function of the terrain determined by 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. By estimating the terrain characteristics as the robot drives paths can be adapted to explore the environment and optimise energy usage.

Much previous work has focused on mapping obstacles however outdoors in unstructured terrain 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. We consider two classes of obstacles: hard and soft hazards [Karumanchi, 2010]. Hard hazards are obstacles that can never be traversed, for example a wall, and methods for detecting and avoiding these obstacles are well covered in prior literature [Borenstein and Koren, 1989; Stentz, 1993]. The second class is soft hazards, regions that can be driven over but at increased cost in terms of energy usage. In our previous work we have mapped these soft hazards and figure 1 shows an example energy usage mapped offline with candidate paths. In this case the optimal path would be path C which is a longer path but uses less energy as it is mostly on hard sand near the waterline. Prior work has also investigated the simulated exploration and adaptation of paths but no results have been presented for online adaptation from sensed data.

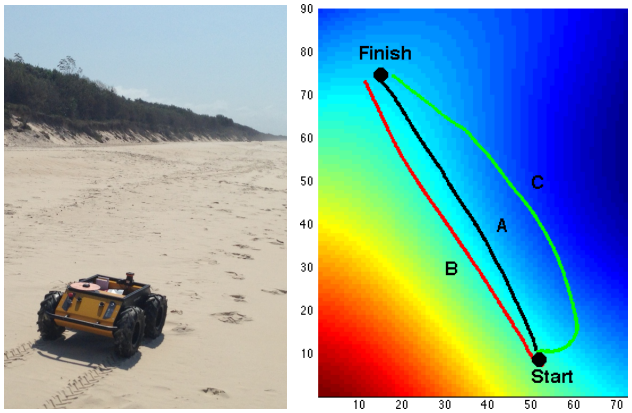

Figure 1: Previous work has used the Clearpath Husky to map a beach using proprioceptive sensors, in this case energy consumption, gathered offline. The resulting traversability maps showed an increase in power usage as the robot moves away from the waterline to softer, more difficult to traverse sand.

In this paper we demonstrate an approach to the problem of terrain exploration and mapping that we show is capable of energy efficient exploration and touring of environments on a small scale robot. Leveraging existing work we can

build spatial maps of traversability, based on the robot's experience, that can be used for planning minimal-energy cost paths. Direct experience 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 hotel load of sensors and computation.

Previous work has examined the ability to generate these maps but has not presented a practical demonstration of this approach. The key contribution of this work was to show a small scale robot conducting online exploration and mapping that achieves comparative results to simulation. A simple scenario was used to demonstrate the convergence and achieved an energy-efficient exploration strategy. Our motivating scenario was a robot performing repeated tours of a set of waypoints and previous research has demonstrated results and statistics generated using Monte-Carlo techniques to show the efficacy of this scheme.

The paper is structured as follows. Section 2 presents a summary of related work. Section 3 describes the techniques for mapping traversability used in prior work and details the simulation environment. Section 4 presents the experimental setup for validation of prior work and section 5 details the simulated and experimental results on a small scale robot. Finally, Section 6 summarises our conclusions and discusses directions for future work.

2 Background

Traversability is the cost of driving through a region and is also known as drivability, trafficability, navigability, coverability, terrainability, manoeuvrability and mobility [Papadakis, 2013]. In this paper we use motor power as a measure of traversability but a range of methods for measuring and estimating traversability have been proposed in prior literature. Traversability metrics can estimate the cost of terrain directly from sensor data or by classifying terrain into one of a number of known classes (eg. concrete, grass, gravel, etc) of a priori known cost. 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.

As many robots are fitted with spinning and nodding lidar or stereo vision the 3D structure of the terrain is commonly used to calculate traversability. Implementations range from simple surface roughness-based traversability metrics [Castelnovi *et al.*, 2005], to adapt the speed of mobile robot to the terrain immediately in front of it, to metrics that use global elevation maps or roughness to determine the cost to cover a region or drive a path [Molino *et al.*, 2007]. Roughness has also been used by rover style robots using [Singh *et al.*, 2000] to determine local roughness or slope to plan paths that avoided rocky and sloped areas.

Figure 2: The loose grave and sand surfaces (left) have a high cost in terms of traversability yet are visually similar to the low cost exposed aggregate concrete and concrete path (right).

2.1 Classification

In structured environments terrain will often belong to a set of known classes. In these environments classification can identity the terrain type and by assuming homogeneous terrain properties these can be used to inform path planning. For classification imagery has been the most popular sensor modality and terrain classification has been performed using colour analysis [Ulrich and Nourbakhsh, 2000; Kim *et al.*, 2006], learning [Howard and Seraji, 2001] and feature based methods [Khan *et al.*, 2011; Filitchkin and Byl, 2012]. Colour analysis makes strong assumptions between colour and terrain making it unsuitable outside structured environments. Learning and feature based methods are more flexible but are still susceptible to ambiguous terrain such as that shown in figure 2.

Classification is often simplified to a binary obstacle classification to determine whether terrain is locally traversable or not, leading to the well known occupancy grid representation. This type of traversability classification has been demonstrated using a neural-network-based approach [Konolige *et al.*, 2009; Shneier *et al.*, 2009] and other learning methods [Talukder *et al.*, 2002]. This is valuable for hazard avoidance but does not provide more nuanced information about the cost of moving across regions.

Classification relies on known terrain costs from measured terrain properties or expert knowledge. It also assumes no intra-class variation, or homogeneous terrain, which does not apply for most natural terrain types. To improve classification and to allow it to adapt to unknown terrain types it is often augmented with proprioceptive sensors such as the wheel slip, vibration and energy consumption. This can infer whether or not the classification was successful and to potentially update the cost associated with the terrain class.

A novel approach to self-supervised classification was demonstrated by Angelova et al. that used onboard stereo im-

agery to determine a local traversability map and used estimated vehicle slip to supervise learning of the terrain classification. The work of Bagnell et al. extends Silver et al. to include learning the association between local traversability and the classification from satellite imagery. 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.

2.2 Proprioceptive sensing

Extroceptive sensors all have their individual weaknesses. Sensors that map terrain structure, such as spinning or nodding lidar are expensive, bulky, heavy and power hungry which can be problematic for small, low cost or long endurance robots. Ambiguous and unknown terrain types will always be a problem for methods that rely on a strong a priori correlation between sensor measurements and terrain cost. Proprioceptive sensors directly sense the robot's experience avoiding the assumptions and inference required for the approaches above.

Methods using only proprioceptive sensors have been demonstrated for terrain classification [Giguere and Dudek, 2009] and have also been used to characterise terra-mechanical properties [Ojeda *et al.*, 2005]. In prior work [Martin *et al.*, 2012] 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 the motivation was to optimise energy efficiency and this was done by recording proprioceptive sensors, specifically motor power usage, and incrementally mapping traversability as the robot drives.

3 Prior Work

Our previous research has examined the problem of visiting a set of desired waypoints, otherwise known as a tour, as often as possible given the finite onboard energy. This requires minimization of energy used per tour. The robot must incrementally explore and learn the relationship between location and motive power usage, to find an optimal path for visiting the waypoints. Assumptions made include: the robot was always localised; waypoints could be visited in any order; and the robot had sufficient sensors to measure local traversability online.

Formally the problem is expressed as finding the path $\mathbf{x}$ which minimises the total energy consumption, E_t, for a 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 terra-mechical properties; 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.

3.1 Gaussian Process Regression

As the robot traverses the region it gathers samples of motive power usage. We utilized 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

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

where k describes the relationship between observations at $\mathbf{x}$ and $\mathbf{x}'$, and where σ_f and l are learnt hyper-parameters. 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 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 in discontinuous or rapidly changed scenarios can produce over-smoothed data [Vasudevan *et al.*, 2009].

Long term operation will result in unbounded increase in data points and as GPs typically scale $O(n^3)$ [Rasmussen, 2006], where n is the number of samples, this will eventually make recomputing the costmaps with GPs intractable. To prevent this we bin the data points into terrain cells similar to the method proposed by Plonski et al. . This 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.

3.2 Path Planning

The D* algorithm [Stentz, 1993] is used for path planning and D* distance cost maps are also updated at the end of a tour when new traversability information becomes available. When more than one waypoint is visited the cost for traversal is estimated using the D* algorithm for each pair of waypoints and the travelling salesman problem is solved to determine the best order to visit the waypoints. An exact solution to the

travelling salesman problem was computed given a low number of waypoints however an approximate solutions, such as those in Russel & Norvig , could be used for larger networks.

For the first tour the robot plans a naive shortest distance path to each of the waypoints. Upon returning to base, motive power information gathered during the tour is used to generate a new estimate of the traversability map using the GP regression. 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. As the robot completes each tour its knowledge of the environment increases. The process is repeated until the robot completes 25 tours or the energy cost E_t converges to a constant.

The GP has the effect of biasing the robot towards exploration as terrain is optimistically assumed to have low traversability in unknown areas. 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. Some areas will not be explored if the cost due to hotel load and the estimated travel cost to reach these regions is lower than a shortest path. The robot will therefore explore different routes until converging to some (locally) optimal path.

A more detailed analysis of the benefits of exploration on a statistically significant number of scenarios is presented in [Martin and Corke, 2014]. This also examines the effect of hotel load on exploration, when exploration is beneficial and how the map evolves in natural terrain.

4 Experimental Setup

In our previous work [Martin and Corke, 2014] we have shown the mapping of terrain using proprioceptive sensors and demonstrated convergence to an optimal path in a simulated environment. This section describes an online implementation in a simplified scenario to show exploration and converge to an optimal path using sensed data. We also parametrise a real robot and compare the simulated and experimental results.

Two factors make the problem of demonstrating online operation difficult. The requirement of the vehicle to operate for a long continuous period and obtaining ground truth for proprioceptive sensors. To validate our approach prior to implementation on an outdoor mobile robot, we have used a small scale robot. This implementation allows us to control a number of factors, which are assumptions made in the simulation environment, namely that the terrain is flat, has a known cost and that the vehicle is always localised. It also allows the results from simulation and experimentation to be directly compared to validate the simulation environment and the efficacy of our approach to exploration.

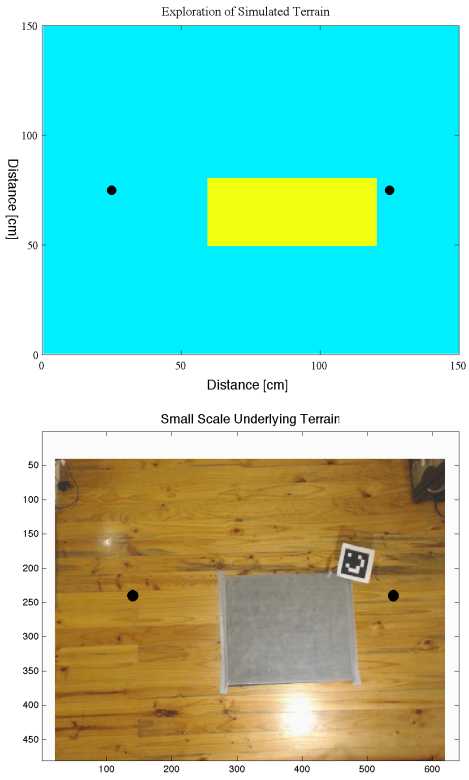

Figure 3: Overhead view of both simulated (top) and real (bottom) exploration environments. The robot is tracked by an ARTag on top of the robot.

In order to limit variables a very minimal environment was chosen. This was a constant low cost with an area of high cost blocking the shortest distance path. The desired result was to have the robot map the area and converge to a path which skirts the high cost area resulting in a slightly longer but minimum energy path.

For the experiment we used a custom build four wheel drive robot approximately 100 mm cubed. The low cost terrain was represented by a smooth timber surface and the high cost terrain by the grey carpeted area. We characterised the real robots power usage as 0.21 W of hotel load. The robot was moved at $0.1\,\mathrm{m/s}$ and the power usage measured at 0.63 W on the low cost terrain and 1.21 W on the high cost carpeted area. These values were used to construct the simulation environment with the equivalent hotel load, P_h and terrain currents P_m. No obstacles were included in the experiment or simulation.

To track the robot we used the Aruco tracker [Garrido-Jurado, 2014] and a Logitech C920 webcam. The location of the robot is updated at 30 Hz and the same path planning and path following configuration as the simulation is used.

The robot records its motor current consumption at 10 Hz and the voltage is regulated to a constant 7 V to allow accurate measurement of the power consumption. The velocity is estimated from position and the power consumption normalised by velocity to give a measure of the energy used per meter. All computation is done offboard on a server and the robot is controlled over a wifi link.

5 Results

Figures 4 and 5 show the evolution of the simulated and experimental maps. Both the real and simulated robots converge to an equivalent map of the area. The difference in the two results can be attributed to noise on the measurements.

The current consumption in steady state is low when compared to the initial acceleration. This was not accounted for in simulation and caused the peaks shown at the waypoints in the real experimental data. We also do not incorporate a model of the vehicle energy usage while turning which may contribute to the variation. Despite this with sufficient passes the results converge to a reconstruction that approximates the simulated experiment with no noise.

This experiment was run three times and in all cases the map showed the high cost area and the path converged to a constant path which avoided this area. While the maps are not identical due to noise figure 6 shows that a vehicle with proprioceptive sensing is able to reconstruct the cost of an underlying surface repeatedly and converge to the optimal path within the environment.

The evolution of simulated and experimental tour cost show a similar trend. Figure 7 shows the initial shortest distance path and then exploration over various paths with higher and lower cost until converging to the optimal path. For this experiment the cost of the first tour is 28.7 J and the converged optimal path approximately 16.0 J with some variation due to noise. The cost of exploration to find this path is 206 J over 7 tours compared with 201 J for following the shortest distance path. By the 8th tour the robot is already benefiting from the lower cost of the optimised path despite the cost incurred for exploration.

This experiment shows the efficacy of our approach on a small scale robot. It also demonstrates comparable results to the simulation and that there is benefit to exploration on a real robot. While this is a simple test case we would argue that this demonstrates the feasibility of our approach and validity of the simulation constructed to be equivalent to the Clearpath Husky.

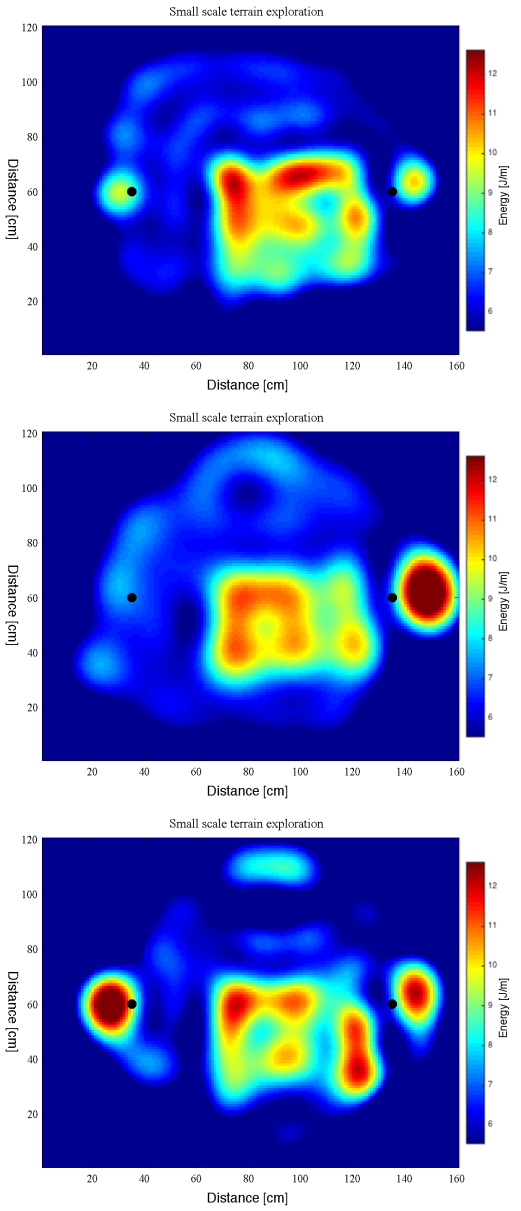

Figure 6: Three experimental terrain map generated after 25 tours through the environment. All maps show the high cost area has been reconstructed.

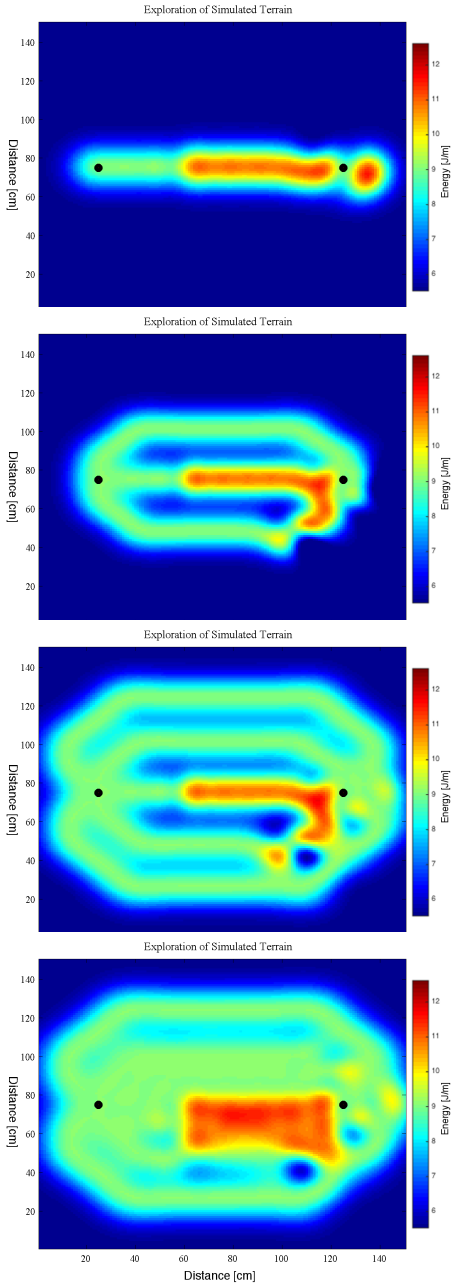

Figure 4: The reconstructed terrain costs for simulated terrain after one (top), three, five and ten passes (bottom). After ten passes the simulation converged to a constant cost for traversal and is terminated.

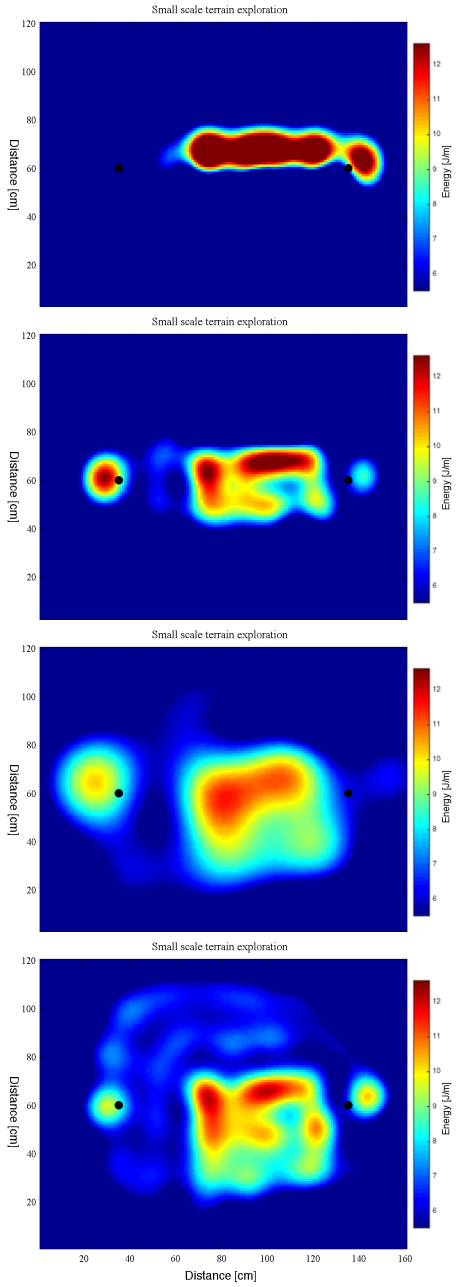

Figure 5: The reconstructed terrain costs for real terrain after one (top), five and ten and 25 (bottom) passes. The termination of the experiment occurs when the cost to drive two successive tours is equal however due to noise on the measurements this criteria was never satisfied but the robot converged to an approximately constant path for tours from 8 to 25. The peaks near the waypoints are caused by high energy usage during the acceleration of the robot from rest.

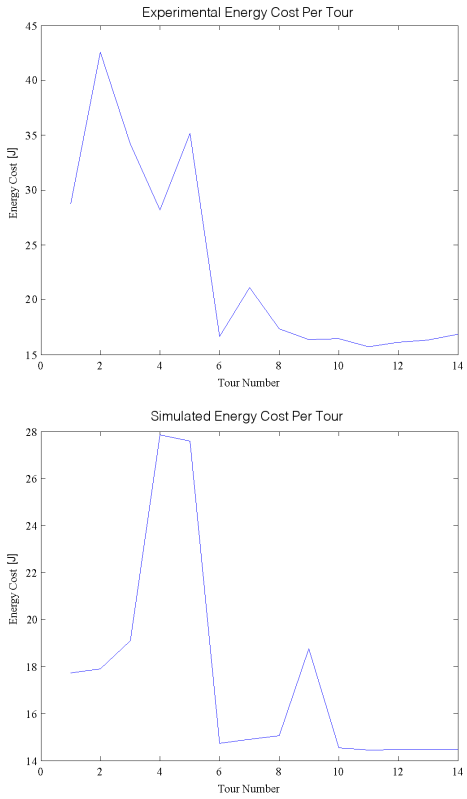

Figure 7: Energy cost of tour for both real (top) and simulated scenarios (bottom).

6 Conclusions

We have presented a system which can explore a terrain with a priori unknown traversability and achieve a minimum energy tour for a set of waypoints or a single goal, with or without obstacles in the environment. We demonstrate the estimation of local traversability, from motive power, can be used to update a GP regression of a global cost map that is used for planning optimal tours. We presented a comparison of this approach in simulation to experimentation for a small scale vehicle and have demonstrated comparable results.

We have shown exploration can improve performance when compared to shortest distance. We have shown robots are able to explore the environment and converge to an optimal path and this is repeatable in experimentation. This validates our simulation in a simple scenario and these results make a strong argument for larger scale experimentation.

6.1 Future Work

This experiment was conducted as a step towards validation of the exploration and reconstruction of terrain prior to deployment on a long term outdoor experiment. Our next step is to deploy the system on the Husky platform and observe 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 the assumption of flat terrain. The energy cost associated with turning is not insignificant for a skid-steered vehicle and this is expected to increase noise on the underlying terrain measurements. Modelling of the vehicle energy consumption with motion and slope will be critical in demonstrating this approach in outdoor environments.

The current planning and exploration strategy has solely used the square exponential kernel with minimal assumptions made about the structure of the data. The repeatable small scale experiment presents an ideal scenario to conduct research into the effects of different kernels and assumptions beyond pure simulation. We have also examined the effect of varying hotel load in simulation and how this effects the degree of exploration and we intend to conduct a similar experiment on the small scale system.

Finally 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. We intend to examine the effects of step and gradual changes in the environment both experimentally and in simulation.

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