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On Traversability Cost Evaluation from Proprioceptive Sensing for a Crawling Robot

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Abstract. Traversability characteristics of the robot working environment are crucial in planning an efficient path for a robot operating in rough unstructured areas. In the literature, approaches to wheeled or tracked robots can be found, but a relatively little attention is given to walking multi-legged robots. Moreover, the existing approaches for terrain traversability assessment seem to be focused on gathering key features from a terrain model acquired from range data or camera image and only occasionally supplemented with proprioceptive sensing that expresses the interaction of the robot with the terrain. This paper addresses the problem of traversability cost evaluation based on proprioceptive sensing for a hexapod walking robot while optimizing different criteria. We present several methods of evaluating the robot-terrain interaction that can be used as a cost function for an assessment of the robot motion that can be utilized in high-level path-planning algorithms.

Keywords: terrain traversability, proprioceptive sensing, walking robot.

1. Introduction

Exteroceptive sensing is widely analyzed and summarized in the survey [1], where authors conclude that the most favored method is to assess the traversability characteristics *before* actually driving the robot into the respective region. Such an assessment is based on a terrain model created from exteroceptive sensors like laser range finder or stereo camera.

However, the difficulties a robot has while traversing rough terrain (e.g., slippages, softness of the ground, energy consumption, etc.) cannot be foreseen in advance. One has to actually walk through the terrain to feel and measure the interaction between the robot and the ground using proprioceptive sensors like accelerometers, force and torque sensors, etc.

According to the survey that provides a study of unmanned ground vehicles (UGV), the generic capability of a robot to negotiate the terrain is the most commonly called as the *traversability* (along with occasional terms like *terrainability, trafficability, mobility*, etc.). Based on that, we follow this established term and refer to its value as to the *traversability cost.* Although the cost is a common name, its meaning varies among researchers. Regarding the mission the robot is requested to accomplish, we need to balance between the time or the distance traveled, the energy consumption, the stability, the danger along the path, etc.

Having a terrain model, a common method of optimizing the traversability cost is to prefer a smooth and obstacle-free path, but a usage of proprioceptive sensors as indicators of the expected cost does not have such a common direction. In this paper, we report on existing approaches for traversability assessment based not only on exteroceptive sensors but we rather focus on proprioceptive sensors. Moreover, instead of *wheeled* robot, we consider *legged* robots.

The rest of the paper is organized as follows. We identify the main components of the terrain traversability analysis in Section 2. First, we provide a brief overview of the exteroceptive sensing based methods for a comparison. Next, we follow with an overview of known approaches using proprioceptive sensing. We formulate the main objectives in the view of the terrain traversability evaluation in Section 3 and propose traversability evaluation methods for walking robots while focused on utilizing proprioceptive sensors in Section 4. Finally, a discussion about possible future approaches is given in Section 5.

2. Related Work

A great progress in the field of autonomous, perception-based, off-road navigation in robotic unmanned ground vehicles (UGV) was influenced by the DARPA Learning Applied to Ground Vehicles (LAGR) program [2], which ran from 2004 until 2008. The challenge evoked several solutions [3–5] with different approaches of robot sensing which can be divided into two groups as: 1) exteroceptive; 2) and proprioceptive sensing.

2.1. Exteroceptive Sensing

It is reasonable to have information about the terrain prior to traversing it. Laser scanner and camera are examples of exteroceptive sensors mostly used in the case of acquiring terrain characteristics. The terrain scan can provide an elevation map for a proper foothold planning [6] and estimation of its traversability [7] using a laser scanner. Characteristic features can be obtained from a far-field scan (color image, stereo camera, etc.) and classified based on a model learned from near-field [3, 4, 8] where more data are available. With data source getting closer to the robot, we get more precise models of the terrain, but usage of only exteroceptive sensors does not provide much information about the real interaction between the robot and the terrain being traversed and thus the robot can hardly learn from its experience.

2.2. Proprioceptive Sensing

On the other hand, the robot needs to receive a feedback from the terrain to utilize learning from experience. Proprioceptive sensors measure the modalities of the terrain that affect the robot motion directly.

In the path planning task, the robot plans according to estimated traversability costs. However, the estimation can change when the robot actually encounters the terrain, as it has been applied in the previous approaches [3, 4, 8] using wheeled robot with bumpers, wheel encoders for a slip measurement or IMU with gyros and accelerometers for measuring the roughness of the terrain. For example, a tall-grass area can be estimated as a non-traversable using only a range measurement, but it turns out that the robot can go through it without a significant difficulty.

The traversability cost assessment is closely related to the terrain classification (or discrimination) assuming that the terrains of the same kind provide the same conditions for traversing. Based only on proprioceptive sensors, the classification can be done using accelerometers [9] (the faster the speed, the better the accuracy) or yaw-angle variations [10] on a wheeled robot, or using servo drives feedback on a hexapod walking robot [11, 12].

Focusing now mainly on legged robots, an early analysis of terrain traversability for legged locomotion using active perception was proposed by Krotkov back in 1990 [13] studying the terrain stiffness and surface friction upon foot contact on a planetary rover – the Ambler robot. However, the final path of the Ambler robot is computed on a grid terrain elevation map avoiding occluded cells [14], i.e., without the possible knowledge gained from the proprioceptive sensors.

A more matured solution [15] utilizes a biologically inspired gait on a hexapod crawler. Carrying a lot of proprioceptive sensors, the robot was able to negotiate small obstacles using few hard-coded reflexes which ensured quality footholds during the motion. However, the estimation of the traversability cost relies only on exteroceptive sensors and the shape of the terrain.

Regarding our focus, we consider the work of Hoffmann et al. as the most related to our approach. They presented how different sensory modalities affect the accuracy of the terrain discrimination using a quadruped Puppy robot [16]. They also studied the relationship between the gait used and the classifier accuracy [17] including using sequences of different gaits to get better results.

3. Problem Statement

The terrain sensing and the evaluation of the traversability cost of the robot motion fits into the scope of path planning. Assuming we have a map of the environment in terms of positions of untraversable obstacles or regions, we can build a weighted graph on top of the map. Although we consider evaluation of the cost for path planning, the planning itself is out of the scope of this paper. Therefore, we consider the planning problem can be solved using optimal planners like A* [18] or D* [19] on a graph with known weights, i.e., the costs on the edges. The path consists of a sequence of actions (the robot moves along an edge using a particular gait) that have some cost—the traversability cost—which can be computed from various sources based on different criteria and different tasks the robot is performing.

In general, we can distinguish sources of information the robot receives (terrain-sensor modalities) and the outcomes of the resulting robot motion (cost modalities) as can be seen in Fig. 1.

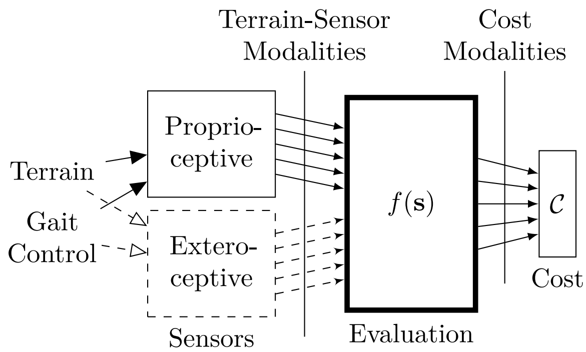

Figure 1. Schema of the robot perception module. The input modalities represent different sensor measurements of the terrain which are used in a function f to evaluate the traversability cost $\mathcal{C}$. The cost is multimodal in general but usually only one modality is used for planning (e.g., the robot speed).

We can imagine that a terrain can be described by several characteristic features: shape, consistency, temperature, friction, etc. which can be measured by various sensors. Each such a feature can be viewed as a modality that is either directly measured or remains hidden. Each sensor refers to different modalities and combined together, we get a set of observable modalities on the input side of the robot perception module generating a multidimensional vector of sensor data. In general, we can say that more modalities—and hence more information—about the terrain we have, the better the estimation of its traversability cost we can get. Notice that some of the modalities may provide more useful information (regarding the cost evaluation) than others.

The output side of the module is also multimodal although it is not as obvious because usually only one modality is used for the traversability cost estimation (e.g., the robot speed while traversing the terrain).

The main problem is the middle part (of the schema in Fig. 1) that consists of an evaluation function f which transforms the sensory measurement into a single (albeit multimodal) cost. The methodology how to extract a single cost from a lot of data in time, frequency or other domain is not a straightforward task and hence results vary among researchers from the simple and obvious findings to more and more sophisticated methods.

3.1. Terrain-Sensor Modalities

The input modalities refer to the robot-terrain interaction from which we can gather the sensory data. However, we can gather such data only from the observable modalities. For example, without a camera image, we can hardly determine the color of the terrain. A (certainly not complete) list of terrain-sensor modalities should include following terrain features:

- *Shape (surface)* – The 3D shape of the terrain or obstacles is useful for precise motion planning and it is usually scanned by exteroceptive sensors but can also be inferred from an advanced touch sensor.
- *Color* – A color camera image of the terrain area can enhance the terrain discrimination (e.g., flat sand vs. concrete).
- *Consistency* – A gravel, snow or sand is not a solid terrain and its surface is usually changed during and after the robot motion while leaving trace or marks on such terrain. This can be measured by sensible touch sensors or by comparing the surface shape before and after the motion referring to the terrain changeability or granularity.
- *Softness* – Differences between solid (e.g., concrete) and soft (e.g., carpet) terrains can affect greatly the robot performance. This modality is measurable only by proprioceptive (e.g., force) sensors.
- *Compliance* – A terrain can look stiff (e.g., grass or small branch) but does not resist to the robot motion and usually regains its shape afterwards; so, a compliant terrain is penetrable. This is also measurable only by proprioceptive sensors.
- *Adhesion* – An adhesive terrain offers better friction and hence better traction which is crucial to ensure stable footholds and permit high accelerations. A force sensor or slippage analysis is needed to measure the adhesion with respect to the robot leg shape and material.
- *Temperature* – In some cases, e.g., on a volcano, a robot might need to avoid hot surfaces in order not to damage itself. The temperature (scanned by a thermal camera) can also be used for a better estimate of terrain traversability by analysing the relations between the terrain granularity (compactness) and thermal transients [20].

As it is shown in Fig. 1, the values of input modalities measured by exteroceptive sensors are (in general) dependent on the terrain being scanned and also on the gait that drives the robot. The sensor readings can be affected when using a different gait—e.g., a fast tripod gait causes shaky motion of the robot and the images taken can be blurred. Similarly, when measuring by proprioceptive sensors, some of the terrain-sensor modalities can change its value depending on the robot motion. For example, the terrain can seem solid and adhesive while traversing slowly, and crumbling or slippery when accelerating (on gravel or ice). Another example for a wheeled vehicle is a sand (desert) that can be traversable until a small change in the control is applied and then it become completely untraversable.

Focusing on proprioceptive sensors and legged robots, the most important terrain-sensor modalities are those which directly affect the robot motion and hence its performance: *shape, consistency, softness, compliance*, and *adhesion*.

3.2. Cost Modalities

In general, the outcome (or the cost) of the robot motion does not have a single scalar value. For example, answering a question: “How was the robot going?” with “5” looks like some information has been lost. Instead, for example, we would like to know that it went fast but spent a lot of energy and hit several obstacles along the way. The crucial part is then to balance the trade-off between all of the possible outcomes—the cost modalities— of our interest. The outcomes (cost modalities) can be the following (again, we do not claim it is a complete list):

- *Average speed (time)* – The overall time and speed has to be evaluated relatively to the robot capabilities. Either a reliable odometry or external motion capture system is needed for a proper evaluation.
- *Energy consumption* – A robot might have a limited energy capacity to fulfill its task, and therefore, it needs to care about the energy consumption (e.g., to switch to a more energy-efficient gait [21]).
- *Maximal torque* – In very rough terrains, the balance in exploiting all motors the same can be impaired and very high torque values of some motors can cause overheating or damage of servos and the robot itself.
- *Uncertainty of localization* – Continuous robot body motion—if not smooth enough—can negatively affect the reliability of range sensors or camera-based visual localization.
- *Stability risk* – The robot posture can be close to its stability margins during the motion, which increases the risk of falling and should be counted in further path planning.
- *Damage risk* – A precise terrain analysis can unveil risky areas where the robot can be damaged (e.g., after a small slip), and therefore, these areas should be either avoided or at least considered.

Notice that the aforementioned cost modalities are dependent not only on the terrain the robot is traversing but also on the gait that is used to control the robot (except the risk of damage from a prior terrain analysis to avoid such a terrain).

The traversability cost is usually evaluated using only a single modality when a robot is performing a simple task. However, if the robot has to perform a long-term mission and meanwhile learn from its own experience to achieve better results, a single modality is not enough and the other modalities have to be considered. A robot can then optimize its decisions in order to keep a high performance in a long period.

4. Use Case

The proposed discussion of multiple modalities on both the terrain-sensor interface and the evaluation of the traversability cost can be applied on almost every mobile robot. However, each robot has different set of sensors and thus it can measure different terrain features and thus measure different cost modalities. Here, we present an example—a use case—for a hexapod walking robot operating in a rough terrain with limited proprioceptive sensory data. The platform, used methodology, and testing scenarios are described in the following parts. In Section 4.4, achieved results are presented.

4.1. Used Hexapod Platform

We used an affordable platform *PhantomX Hexapod Mark II* with an adaptive gait [22] that enables this robot to traverse uneven terrains and negotiate small obstacles. The gait is a periodic-based (in terms of alternating the legs in a given order) but alters and reacts on the underlying terrain surface. The robot utilizes its servo drives feedback for the tactile sensing of the ground and servo drives are also the only sensory information the robot has (i.e., the robot is technically blind).

4.2. Methodology of Cost Evaluation

Following the set of possible traversability cost modalities listed in Section 3.2 and the sensors available, we consider only the *speed, energy (power) consumption*, and *maximal torque*. The speed is given from the running time of the experiments and known distance of the traversed path. The energy consumption is estimated very roughly using several approximations. Firstly, the instantaneous energy consumed (the power) is proportional to the drawn current assuming a constant voltage ($P \propto I$). Secondly, the current is proportional to the torque of the servomotor ($I \propto \tau$). Thirdly, the torque is (according to the servo manufacturer) proportional to the servo drive controller position error e, ($\tau \propto e$). Therefore, the power consumption (in a small discrete time step) can be inferred from the sum of absolute values of servo position errors

$$P \propto \sum_{i=1}^{18} |e_i|. \tag{1}$$

For simplicity, we leave the units and scale because we only need to know the relative changes in the energy consumption under different conditions. Finally, the maximal torque is computed similarly as

$$\tau_{max} \propto \max e. \tag{2}$$

4.3. Testing Scenarios

The traversability cost evaluation was tested on three different terrains shown in Fig. 2. The office floor is perfectly flat while the wooden blocks include obstacles with height about 5 cm (for comparison, the leg femur-tibia and tibia-foot links are 7 cm, resp. 13 cm long). The third terrain contains free wooden obstacles (2 cm high) that are not fixed to the floor and thus can be shifted during the robot traversal. The trajectory during experiments was equally long on all of the terrains and the robot was driven by adaptive gait [22] under 3 different configurations (pentapod, tetrapod and tripod).

Office floor — Movable obstacles — Wooden blocks

Figure 2. Terrains traversable by the adaptive gait

4.4. Results

The measured experimental results are shown in Table 1. As can be seen from the speed comparison, the robot is not slowed by obstacles and hence the used gait (in each of the three configurations) is very adaptive. Nevertheless, its speed is slow even on the flat office floor and there can surely be found a faster gait for flat terrains which, however, may not be able to traverse other terrains.

Terrain	Office	Movable	Blocks
Gait	5/4/3	5/4/3	5/4/3
Speed [mm/s]	9/15/22	9/15/22	9/15/22
Work [E/mm]	45/28/19	52/32/23	47/28/21
Power [E/s]	39/42/43	45/48/51	42/43/48
Max torque	47/45/44	53/48/65	62/60/66

Table 1. Different cost modalities experimentally evaluated on different terrains for the same traveled distance using adaptive gait with different number of legs in support phase. Three values in each cell stand for pentapod / tetrapod / tripod gait.

If we look at the traversability cost regarding different modality—the energy consumption, we can see that traversing the flat terrain is the least energy consuming. However, the other terrains have no more than about 10% increase in power consumption. Traversing movable obstacles causes the highest energy consumption, which can be explained considering friction and leg configurations. When a leg slide sideways on a floating obstacle, a more momentum is created on the joints and thus more torque is needed to counteract this behavior. Naturally, it is easier to walk with legs under the body than with legs straddled.

Another perspective of the evaluation is by comparing the maximal torque in the servo drives measured during the robot motion. We can see that the highest torque was measured when traversing the blocks. This indicates that such a terrain causes legs to be occasionally more loaded than others (e.g., after a small slip on the edge of a block), which is projected also into the average energy consumption (which is based on torque values). Regarding the maximal torque values measured, we can also see that the tetrapod gait suffers less from high torque values (caused mainly by slippages), such that the impact after a slippage is not as big as for the pentapod or tripod gait.

5. Conclusion

We have shown that the evaluation of traversability cost, which is an important part needed for path-planning, depends on the modality of sensory data as well as on the modality of the cost itself. Each cost modality represents a different perspective of evaluating the robot performance and we show how sensory data can be transformed into the traversability cost estimation. While different situations need different cost modalities to be considered, in general, we need to find a trade-off between them to assess the cost more appropriately.

We present a use case of the proposed idea in real-experimental evaluation with a hexapod walking robot traversing terrains with various difficulty. Using only a single gait for all terrains might look appropriate according to the measured speed, but considering another perspective can unveil the potential risk of servo damage and switching to another gait (slower, but not the slowest) would be a more suitable solution.

Getting more into the problem of traversability cost estimation in the future work, we would like to take into account another modality—a gait modality. Combined all modalities together, we can better model the perception of the robot which is a key factor in assessing the traversability costs to different terrain areas. Moreover, the perception can be connected to learning and mapping between the terrain features and corresponding costs can be found automatically.

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