Slip Estimation Methods for Proprioceptive Terrain Classification using Tracked Mobile Robots

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Abstract—Recent work has shown that proprioceptive measurements such as terrain slip can be used for terrain classification. This paper investigates the suitability of four simple slip estimation methods for differentiating between indoor and outdoor terrain surfaces, namely: rocks, grass, rubber and carpet. These slip estimates are calculated using experimental odometric data collected from a tracked autonomous ground vehicle and comprise of two instantaneous estimators and a temporal windowing approach. Results show that only the temporal windowing approach shows significant differences across the terrains investigated, indicating that instantaneous measurements are unsuited to terrain classification.

Index Terms—slip estimation, terrain classification, surface differentiation, tracked vehicles, proprioceptive terrain classification

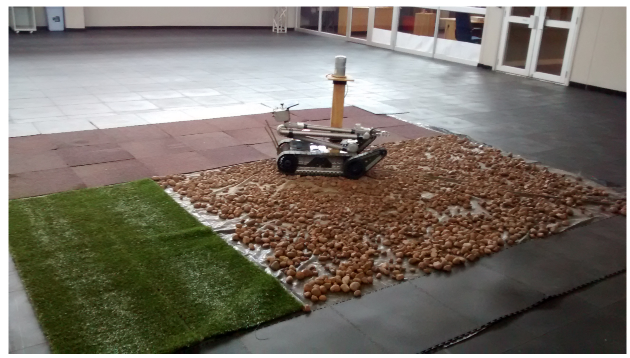

Fig. 1. The layout of the terrain surfaces and the Packbot 510 used for the experiments. The top part is the carpet, grass and rocks are on the sides, while the surrounding area is the rubber.

I. Introduction

In recent years, terrain classification in robotics has become an active field of research. Many applications of unmanned ground vehicles require these vehicles to traverse different indoor and outdoor terrain surfaces. These terrain surfaces contain different properties that affect the driving performance and safety of these vehicles as they traverse terrain. For maximum performance and safety, these vehicles require the ability to detect the change in terrain as they are driving and performing their tasks, so that their control systems can be adapted appropriately [1].

Terrain attributes can also be used to enhance existing soil maps [2], Geographical Information System (GIS) prediction accuracy and conceptual representations of the real world because they provide real spatial entities and not the artificially precise spatial entities that are currently being used in conventional GIS [3].

Terrain classification is the process of determining into which terrain class category a specific terrain patch falls into [4]–[6]. The commonly classified terrain surfaces for outdoor environments are: Dirt, Sand, Clay, Asphalt, Grass and Gravel [7], [8]. In contrast, the commonly classified terrain surfaces for indoor terrain are: Carpet, Ceramic and Linoleum [7], [9], [10]. Terrain classification can be vision-based or through proprioception.

Vision-based classification uses visual features, such as color, texture and shapes, obtained from sensors such as cameras and laser scanners [11]. Proprioceptive classification uses physical wheel terrain interaction features that are extracted from a vehicle's sensors [12]. Proprioceptive classification is sometimes also referred to as contact-based terrain classification [11]. Proprioceptive classification is often used to compliment visual-based classification when different terrains appear visually similar. Proprioception for ground vehicles involves the sensing of the internal states of a vehicle using onboard sensors such as wheel encoders, accelerometers and rate traducers [13] [14].

Wheel slip has been proposed for proprioceptive terrain classification, as it occurs as a result of wheel terrain interaction. When autonomous vehicles traverse different terrain surfaces, the terrain surfaces create a characteristic difference between actual and desired forward and rotational velocity values. This characteristic difference is as a result of slip that occurs as the track interacts with the terrain surface [15].

Vehicle slip is relatively easy to measure, and as a result provides a simple mechanism for terrain classification. However, most work has focused on terrain classification using slip for wheeled mobile robots. In this study, we investigate slip measures for tracked mobile robots.

In this paper slip estimation methods are compared against each other based on their ability to differentiate between the four indoor and outdoor terrain surfaces, namely: grass, rocks, carpet and rubber. These comparisons are performed visually using boxplots, and evaluated statistically using the Kruskal-Wallis analysis method and Mann-Whitney post-hoc tests. This paper is organised as follows. Section II describes the experimental methodology, Section III provides experimental results, and finally Section IV presents conclusions and recommendations for future work.

II. Terrain Differentiation Method

This section provides an overview of the terrain surface differentiation methods compared in this paper. Three slip estimation measures are introduced and discussed, along with the experimental setup, data collection and data preparation process followed. Thereafter, the methods used to investigate the applicability of the slip measures to terrain differentiation are discussed.

A. Method Overview

This paper aims to determine whether simple slip estimation methods can be used to determine a difference between terrain surfaces. The terrain surfaces used for our experiments are a combination of both indoor and outdoor terrain surfaces, namely carpet, rubber mat, grass and rocks. The slip estimation methods investigated use data that was collected from a tracked mobile robot. This data includes a combination of actual (measured) and desired (commanded) forward and rotational velocities, the distance between each track and the pitch circle of the track sprocket. Experimental data was collected using a Packbot 510 mobile robot. The platform has been equipped with an onboard computer and has the following sensors installed: an IMU, three cameras and a 3D Velodyne LiDAR sensor. It operates on a Linux system and uses the Robotic Operating System (ROS). The platform is operated through an in-house mapping application installed on the platform and a user interface, which is installed on a console computer and used to control the platform. Communication between the platform and the console is wireless.

The platform can be controlled in one of three modes. The first mode is manual control using a joystick, while the second mode allows semi-automatic control, where goal locations are manually selected and the platform then automatically drives to the goal location. The third control mode is automatic, where the platform enters an exploration mode and selects its own location goals until all possible locations have been explored. For this experiment, we used the semi-automatic control mode as it allowed the robot to be driven over the terrain of interest more smoothly than in manual mode.

Fig. 1 shows an image of the terrain and tracked robot used for the experiment. The terrain surface setup used for this experiment consists of carpet, shown in the top part of the image, rocks and grass on the sides and rubber surrounding the other terrain surfaces.

Fig. 2 shows the patches where the data points were collected, with the sections representing the four terrain surfaces used for testing in the experiment. The lines within the color coded patches are robot position estimates obtained from a pointcloud matching-based simultaneous localisation and mapping algorithm, representing the platform motion across the terrain surfaces. The lines also show where data points were collected for the experiment. Yellow, red, blue and green colours represent rubber, carpet, rocks and grass respectively.

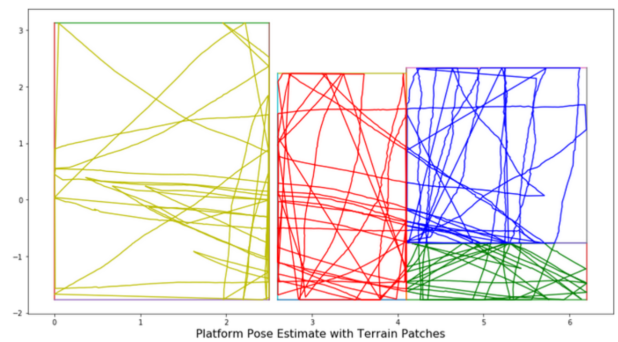

Fig. 2. The figure shows the positions on the four terrain surface patches where data was captured. (Yellow - Rubber, Red - Carpet, Blue - Rocks, Green - Grass.)

B. Slip Estimations Equations

The three methods for slip estimation used for this terrain differentiation experiment are presented below.

1) Differential Drive Slip Estimation: This method is typically used to obtain slip estimates for differential drive mobile robots [16], [17] and has been proposed for terrain classification by [18]. Here, the estimated slip is calculated as

$$i = 1 - \frac{v_d}{r\omega_i} \tag{1}$$

where r is the pitch circle of the sprocket of the tracks, v_d is the desired forward velocity and ω_i the measured rotational velocity of the wheel.

In many cases, the wheel velocity is not measured directly, thus an approximation of the differential drive slip can be obtained using

$$i = 1 - \frac{v_a}{v_d}. \tag{2}$$

Here, i is the proposed measure, v_a is the actual forward velocity and v_d is the desired forward velocity. In this work, we use the velocity ratio directly.

2) Tracked Vehicle Slip Estimation: Equations (3) and (4) provide the slip estimate equations that can be used on tracked platforms to estimate slip when the actual and desired velocities are known [19]. This method estimates the slip for each track, where s_1 is the right track slip

and s_2 is the left track slip. In the above equations, v_d, w_d, v_a and w_a are the desired forward and rotational velocities and the actual forward and rotational velocities, respectively.

$$s_1 = 1 - \frac{2v_a + l\omega_a}{2v_d + l\omega_d} \tag{3}$$

$$s_2 = 1 - \frac{2v_a - l\omega_a}{2v_d - l\omega_d} \tag{4}$$

3) Rotational Slip Estimation: Burke proposed an adaptive slip estimation approach that allows left and right track slip to be computed using only rotational velocity measurements. Here, a recursive least squares estimation process is used to estimate states (5) and (4) using a sliding window of actual rotational velocities and velocity commands [19].

$$\phi_1 = \frac{s_1 - s_2}{l} \tag{5}$$

$$\phi_2 = 1 - \frac{s_1 + s_2}{2} \tag{6}$$

These states are related to the velocities of interest using

$$\omega_a = \phi_1 v_d + \phi_2 \omega_d \tag{7}$$

where ω_a is the measured rotational velocity, v_d is the commanded forward velocity and ω_d is the commanded rotational velocity. Slip estimates can be solved for using (5) and (6), given the estimated states.

C. Data Extraction

The process used to collect and prepare the data used for comparison is explained below.

1) Data Collection: The data used for slip estimation calculations were obtained from the platform as follows. Pose estimates were obtained using a pointcloud-based localisation algorithm, the desired forward and rotational velocities used are values sent to the platform by a path-following controller as the platform transverses the generated path from starting points to the goal locations. The actual forward and rotational velocities are values that are estimated by the platform using a localisation algorithm fusing platform odometry, an inertial measurement unit and pointcloud-based localisation estimates.

Location goals were manually selected using the semi-automatic control mode of the platform in order to traverse the terrain surfaces of interest for data collection. The distance between each track and the pitch circle of the track sprockets was obtained using a measuring tape.

2) Data Preparation: The collected data was measured by multiple sensors at different frequencies. A spline interpolation method was applied to obtain measurements and velocity commands at times corresponding to position measurements, in order to identify which terrain surface the vehicle was on at any given time.

The actual and desired values of the forward and rotational velocities used for the experiment were restricted to only the times when the platform is in motion, travelling forward and not turning on the spot, as reliable slip estimation in these cases is challenging.

D. Terrain Difference Estimation

Our goal is to to determine whether each terrain surface possesses slip characteristics that are unique enough to be used to distinguish between terrain surfaces. We investigate this using two approaches for each slip estimation method. Initially, we investigate the distributions of slip estimates for each terrain visually using boxplots. Here, the distribution of the slip estimates is described using standard descriptive statistics of the values, namely: the mean, median, whiskers (the bottom and top quartiles) and outliers.

Thereafter, a Kruskal-Wallis hypothesis test is used to determine if there is a statistically significant difference between the terrain surfaces' slip estimation measures. Pairwise terrain differences are then investigated using a posthoc Mann-Whitney U test.

III. Experimental Results

Fig. 3 shows the slip distributions for the differential method (2), where the green triangles show the mean of the distributions. The boxplot shows little difference between the grass, carpet and and rubber measures.

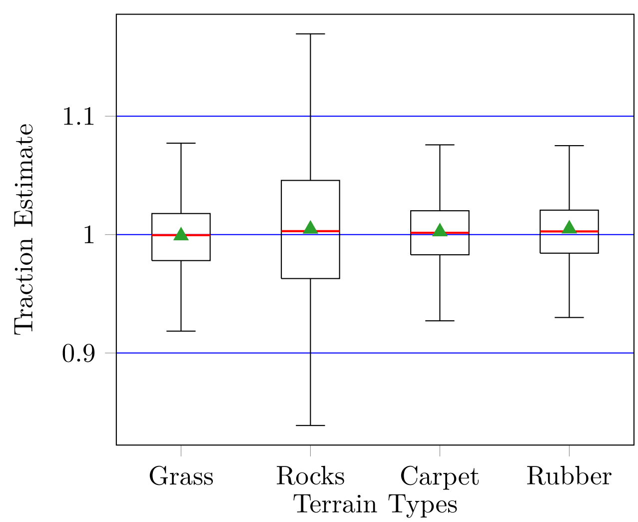

Fig. 3. The boxplot shows the distributions for differential slip estimates.

Fig. 4 shows the data distribution of the tracked slip estimates (3) for the right track, with the green triangle representing the mean of the distribution. The boxplot shows only minor differences between the terrain types.

Fig. 5 shows the distributions slip estimates (4) for the left track. As before, there is little apparent difference in slip measures for each terrain type.

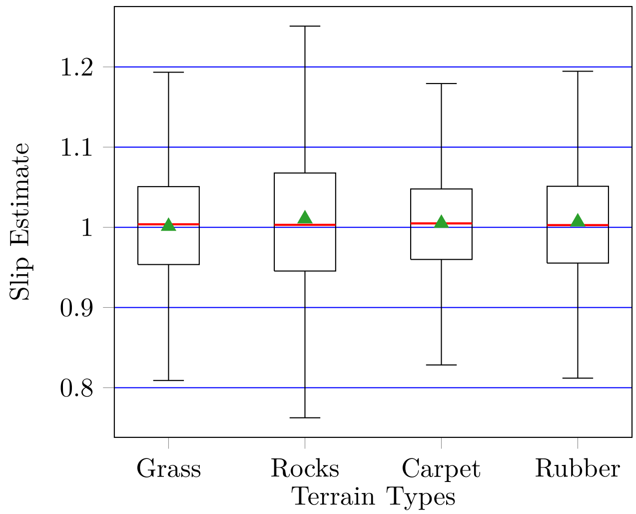

Fig. 4. The boxplot shows the distribution of data for tracked vehicle's right track slip estimation method.

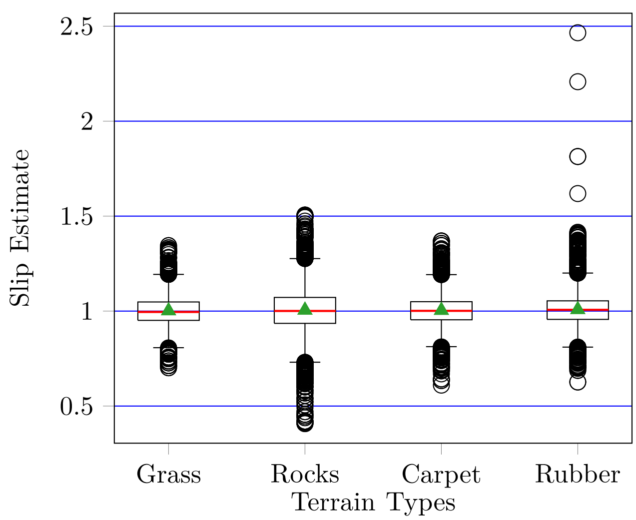

Fig. 5. A boxplot shows the distribution of data for tracked vehicle's left track slip estimation method.

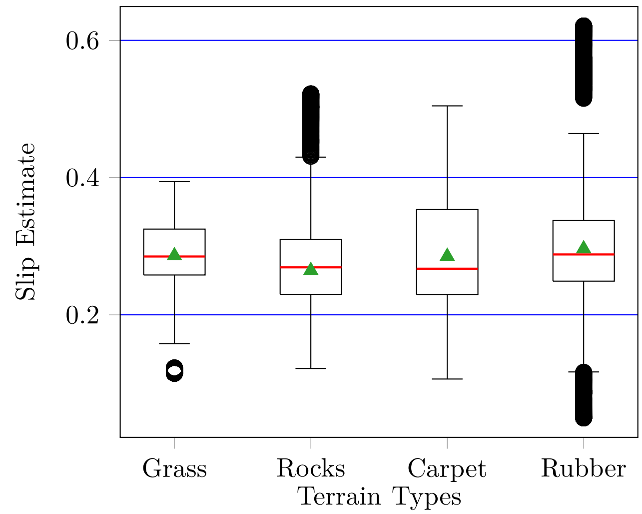

Fig. 6. The boxplot shows the distribution of data for Burke's left track adaptive slip estimation method for each terrain surface for all the sampled terrain surface points.

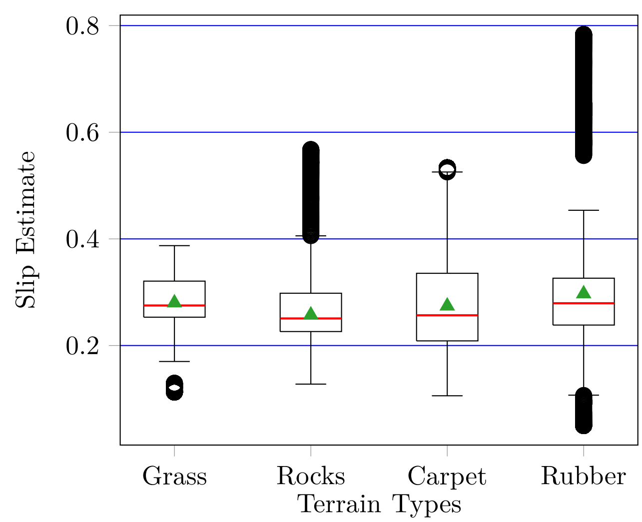

Fig. 7. The boxplot shows the distribution of data for Burke's right track adaptive slip estimation method for each terrain surface for all the sampled terrain surface points.

Fig. 6 shows the distribution of the tracked slip estimates (6) for the left track when Burke's rotational approach was used. The boxplots show clear differences between the terrain surfaces.

Fig. 7 shows the distribution of the tracked slip estimates (5) for the right track when Burke's rotational approach was applied. As before, the boxplot shows clear differences between the grass, rubber, carpet and rock terrain surfaces.

A. Statistical Differentiation

A Kruskal-Wallis hypothesis test was used to determine if the slip measures showed differences between terrain types for each method tested. The tests are further investigated using a post-hoc Mann-Whitney U test.

The Kruskal-Wallies H test showed that there is a statistically significant difference between slip measurements for each of the slip estimation methods ($p < 0.05$).

These differences were further investigated using a set of post-hoc Mann-Whitney tests. The results of the posthoc tests are shown in Table I, II, III, IV, and V, representing the differential slip, tracked vehicle right track, tracked vehicle left track, Burke's right track and Burke's left track slip estimation methods, respectively. The <0.05 alpha values indicate that there is a significant difference between the pair of terrain slips being compared. The >0.05 alpha values shows that the slip measures are unsuitable for terrain differentiation. The alpha value of 1.0 shows that there is no difference in the pair of terrain

TABLE I
Differential Slip Estimation Method

Terrain Surface	Grass	Rocks	Carper	Rubber
Grass	1.0	<0.05	<0.05	<0.05
Rock	<0.05	1.0	<0.05	>0.05
Carpet	<0.05	<0.05	1.0	<0.05
Rubber	<0.05	>0.05	<0.05	1.0

TABLE II
Tracked Vehicle's Right Track Slip Estimation Method

Terrain Surface	Grass	Rocks	Carper	Rubber
Grass	1.0	<0.05	<0.05	<0.05
Rock	>0.05	1.0	<0.05	>0.05
Carpet	<0.05	>0.05	1.0	>0.05
Rubber	<0.05	>0.05	>0.05	1.0

TABLE III
Tracked Vehicle's Left Track Slip Estimation Method

Terrain Surface	Grass	Rocks	Carper	Rubber
Grass	1.0	<0.05	<0.05	<0.05
Rock	<0.05	1.0	<0.05	<0.05
Carpet	<0.05	<0.05	1.0	>0.05
Rubber	<0.05	<0.05	>0.05	1.0

TABLE IV
Burke's Right Track Slip Estimation Method

Terrain Surface	Grass	Rocks	Carper	Rubber
Grass	1.0	<0.05	<0.05	<0.05
Rock	<0.05	1.0	<0.05	<0.05
Carpet	<0.05	<0.05	1.0	<0.05
Rubber	<0.05	<0.05	<0.05	1.0

TABLE V
Burke's Left Track Slip Estimation Method

Terrain Surface	Grass	Rocks	Carper	Rubber
Grass	1.0	<0.05	<0.05	<0.05
Rock	<0.05	1.0	<0.05	<0.05
Carpet	<0.05	<0.05	1.0	<0.05
Rubber	<0.05	<0.05	<0.05	1.0

Mann-Whitney U test results for pair wise comparison in differentiating between the terrain surfaces for each slip estimation method

patches being compared, this occurs when the same terrain surfaces are compared against each other.

The results show that Burke's slip estimation method provided slip measurements that can be used to distinguish between all terrains investigated, for both the left and right tracks. The differential slip estimation method failed to differentiate between the rocky and rubber terrain surfaces. The left tracked slip estimation failed to differentiate between the carpet and rubber terrain surfaces, while the right tracked slip estimation method was the worst performing method.

IV. Conclusion

The suitability of a number of slip estimation methods for terrain classification has been compared in this work. Experimental results showed that slip estimates can be used to differentiate between terrain surfaces. Burke's adaptive slip estimation methods for both left and right tracks proved successful in all the terrain surface differentiation tests conducted, while the other approaches compared failed. This is most likely due to averaging method applied to estimate slip. The instantaneous slip estimation approaches are more vulnerable to noisy measurements as they do not apply temporal averaging.

This work focused on the performance of a selection of slip estimation methods in differentiating between terrain surfaces. Future work will concentrate on the use of temporally averaged slip estimation methods to classify terrain surfaces online as the vehicle traverses the environment and also to detect the change in terrain surfaces.

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