Terrain Characterisation and Gait Adaptation by a Hexapod Robot

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Abstract

Legged robots are especially suited for traversing unstructured terrain outdoors. To maintain efficient locomotion, it is necessary to use appropriate gait parameters informed by terrain interactions such as slipping and sinking. Humans and legged animals inherently use this skill when walking. Effectively characterising the terrain with proprioceptive sensing provides information to the robot control system that can be used to inform a gait optimisation algorithm. This paper presents a novel methodology for any legged robot to characterise the terrain it is traversing in real time. This is achieved by introducing the concept of a time-invariant gait phase. We also develop a method for on-line adaptation of gait parameters such as leg height and stride length based on these terrain characteristics. An experimental evaluation of the real time terrain characterisation methodology and gait adaptation system is presented. The experimental results show that through gait adaptation, the cost of transport can be reduced by up to 69.9% on a carpeted surface and 41.66% on a mulch-covered surface.

1 Introduction

Legged robots offer a number of advantages over wheeled and tracked platforms, particularly on real-world unstructured terrain. These include the ability to walk on uneven surfaces, climb or step over obstacles and adapt gait patterns to improve traction and energy efficiency. In contrast, wheeled locomotion often requires prepared surfaces like roads or rails and offers little adaptability [Raibert, 1986]. The gait patterns that a legged robot can use are defined by a central pattern generator (CPG) which produces a gait using a number of gait parameters including stride length, stride frequency, leg height, etc.

To exploit the adaptability of a robot, sufficient information must be gathered about the environment. To this end, successful terrain classification techniques have been developed for both legged and wheeled platforms using both proprioceptive sensing (sensing the robot itself) and exteroceptive sensing (sensing external stimuli like light or force) techniques [Filitchkin and Byl, 2012; Brooks and Iagnemma, 2012; Manduchi *et al.*, 2005].

Figure 1: The modified PhantomX Hexapod robot used

Terrain classification does not provide robust adaptability. It requires knowledge of similar terrain beforehand, which restricts its usefulness for unfamiliar terrain. Classification makes the assumption that all terrains that humans perceive as 'similar' affect robot locomotion similarly. For example, on a terrain classified as 'grass' the robot-terrain interaction is affected by the density of the soil, the type, length and stiffness of the grass, moisture content, etc. The opposite is also true: where a classification system would discriminate between mulch and gravel, they would likely affect a robot's locomotion similarly.

Terrain characterisation makes no assumptions about the terrain, instead using real time data to inform some general model of locomotion. One of the limitations of characterisation is that there is a large volume of time-domain data to analyse and few run-time approaches to analyse it. With useful data, adjustments to the current gait parameters could be made to suit any terrain changes, rather than choosing from a pre-programmed gait.

Gait adaptation in legged robots has seen some research on RHex and RHex-like platforms [Weingarten *et al.*, 2004; Allen *et al.*, 2003] and in quadrupeds without a predefined gait [Lewis and Bekey, 2002]. Using terrain information to switch or adapt gaits has been accomplished in vertical climbing robots with foot-mounted force sensors [Haynes and Rizzi, 2006], similar hexapods using energetics [Kottege *et al.*, 2015] and in simulation [Mazzapioda and Nolfi, 2006]. To use terrain characteristics to adapt the gait, a general model of the interaction must be developed. The parameters of the model should be found at run-time. Such systems have been realised on wheeled platforms [Wenzel *et al.*, 2006; Dakhlallah *et al.*, 2008].

The system proposed is a novel approach to terrain characterisation for any legged robot with a periodic gait where motor feedback can be obtained in real time. Terrain characteristics are used to generate parameters for a model of the terrain interaction. Ideal gait parameters are then calculated using the terrain model.

2 Related Work

There has been little work in terrain characterisation for legged robots because of the maturity of terrain classification and the current state of technology readiness for traversing truly difficult terrain, but there is a volume of work that is relevant for defining features of the terrain and for making assumptions about the terrain from proprioceptive input. These are particularly prevalent in wheeled applications [Iagnemma *et al.*, 2002; Ojeda *et al.*, 2006a; Bauer *et al.*, 2005].

Terrain characterisation methods using tactile sensors have been developed for wheeled robots [Iagnemma *et al.*, 2004]. These systems utilise z-axis vibration in the suspension system to characterise the terrain, allowing a rover to adapt its velocity and direction. This is effective for wheeled robots but not for legged robots which move much slower and for which more intuitive characteristics exist such as foot contact forces.

Using tactile information has been shown to be useful for terrain classification. Contact locations, object shapes, contact forces and torque response can be found by classifying information from external tactile sensors [Howe, 1993; Lee and Nicholls, 1999]. This requires the use of an external sensor.

In legged robots, proprioceptive terrain classification has seen more research than terrain characterisation, particularly utilising tactile sensors and energetics [Kottege *et al.*, 2015; Walas, 2013]. This shows that proprioceptive techniques are valid for assessing terrains in legged robotics.

The 'RHex' robot platform has seen concentrated development because of the simplicity of its motion. Recently a terrain classification system was successfully developed [Ordonez *et al.*, 2013] using frequency domain features of the z-axis acceleration of this platform, valid because of its legs operate more closely to wheels. Previously, a system for gait adaptation was realised for RHex [Weingarten *et al.*, 2004] using specific resistance as a terrain characteristic. The single degree of freedom in the RHex platform legs show a limitation in the platform when compared to other legged robots that means that this system cannot be applied to any legged robot.

Using only sensory feedback for gait adaptation has been achieved in simulation [Mazzapioda and Nolfi, 2006]. It has been shown that based on neural controllers storing information from all legs, the most effective gait can be selected from some set of predefined gaits.

Characterisation of the terrain interaction using actuator characteristics rather than external sensors and the utilisation of this information to control the gait of a legged robot is, to the best of our knowledge, unexplored.

The work most similar to that presented here is a terrain classification method for a hexapod platform in [Best *et al.*, 2013], which grouped joint position error data (equivalent to torque) according to where in the periodic movement the error was recorded. The system was able to successfully classify the terrain. With knowledge of the classification of the terrain, an appropriate gait could be adopted that had been previously determined to be most efficient for traversing that kind of terrain. A similar approach to data has been taken in this paper, applied to terrain characterisation rather than classification, that employs the same data collection and grouping method to receive general information about the terrain in a form intuitive to a robot. Using this these intuitive terrain characteristics, a run-time gait adaptation system is proposed and evaluated, in contrast to the method of adopting pre-defined gaits.

3 Terrain Characterisation System

3.1 Gait Phase

As a legged robot walks, its movement is unpredictably affected by the terrain. To estimate how the movement is being affected, unsynchronised data from each motor has to be analysed, which can quickly become intensive even on basic legged platforms. This computation can be simplified and made more intuitive by exploiting the periodic nature of legged locomoton.

The pattern of a legged robot's stride is shown in Figure 2. The leg nomenclature is analogous to that of a human leg, with the coxa and femur joints acting like that of a hip joint and the tibia joint acting like a knee. Each period contains a lift phase, a lower phase, and a support phase. This pattern repeats for as long as the hexapod is walking. Data gathered from any sensor can be synchronised with this motion using its time stamp

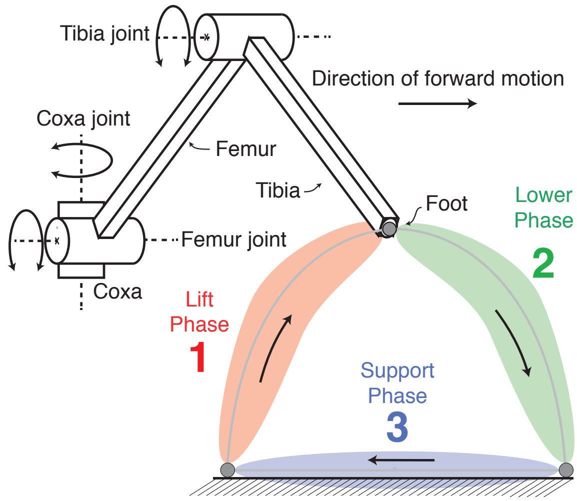


Figure 2: The different stages of leg movement during one gait period and the nomenclature of a hexapod leg.

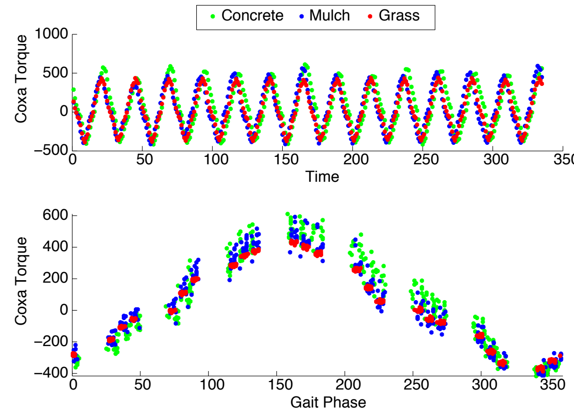


Figure 3: Time-series signals that are messy and unwieldy can be moved to the gait phase domain for intuitive analysis.

and attached to one of these phases. The entire period containing all three phases is referred to as the 'gait phase'. The beginning of the gait phase is arbitrarily set to the transition between the support and lift phases.

In the case of torque data from the coxa joint, overlaying data in the time domain to compare terrains provides almost no discrimination between them. This is the upper plot in Figure 3. It would be difficult to make predictions about how best to adjust the robot's gait for efficiency using data analysed in this way.

The gait phase domain provides a simple visual representation of the data. By mapping this data to the gait phase, how the terrain interactions affect the motor torque become obvious and gaps in data collection are apparent (the gaps in Figure 3 are due to the on-board microcontroller swapping between sending commands to the servo motors and sending data to the recording computer over serial. It is a limitation in the platform but also stands as an example of the kinds of system failures that operations in the gait phase can overcome). This is the lower plot in Figure 3.

The gait phase itself can take any value between 0 and 360 and time-domain data is assigned a gait-phase value based on when it was taken and the position of the foot. The gait phase domain provides a simple visual representation of the data showing that during the support phase (180-360 in the gait phase), the torque usage in the coxa joint is higher on a concrete terrain than on grass or mulch, but the opposite is true during the lift and lower phases (0-90 and 90-180 in the gait phase, respectively). This is because grass and mulch have loose obstructions above the point where the foot rests (i.e., bark and vegetation), providing a force that must be overcome while the foot is stepping forwards. They are also soft underfoot and so the motor requires less torque to move the foot.

The gait phase cannot be defined by the foot's actual position as this signal will vary with uneven terrain. Instead, the 'goal position' of a servo can be used, as this signal is guaranteed to be periodic. Specifically, the goal position wave of the front-left coxa joint is used, as in [Best *et al.*, 2013].

With the gait phase defined in this way, information from every servo can be synchronised with the sinusoidal movement of one leg. In the gait phase domain, patterns in servo information become obvious and terrain information analysis is vastly simplified. Figure 3 shows that as a hexapod walks from grassy terrain to mulch and to concrete, recorded torques in a coxa joint yield consistent patterns at different points in the gait phase, but in the time domain are undiscriminated or distant in time.

The gait phase is completely independent of time, since it is directly mapped to one period of the reference actuator's motion. Therefore, data mapped to the gait phase domain becomes speed independent; data is immediately comparable regardless of the robot's speed, and data collected with low frequency is still useful since it can be associated with a specific part of a leg movement.

With the grouped data further subdivided using the sections of the gait phase in Figure 2, the exact interaction that the hexapod's individual joints are experiencing with the terrain can be characterised. This use of the sections of the gait phase is the basis for the proposed terrain characteristics. By exploiting data in the gait phase domain, these characteristics are speed invariant, require no prior knowledge of the terrain, and make no assumptions about the type of terrain the hexapod is attempting to traverse.

3.2 Defining Terrain Characteristics in the Gait Phase

Mature development in wheeled locomotion has yielded several frameworks for characterising the movement of a vehicle. Analagous characteristics for legged platforms are proposed: slippage, sinkage and resistance.

Wheel slippage detection has seen significant progress and has resulted in robust, complicated systems [Ojeda *et al.*, 2006b; Khan *et al.*, 2015]. There has also been successful slippage detection in legged robots [Hörger *et al.*, 2014]. Slippage can be detected by examining the support section of the gait phase, particularly in the coxa joint.

Detection of sinkage has also been shown to be important for the motion of wheeled vehicles. For hexapod legged platforms, sinkage can be detected in the lower and support sections of the gait phase, most evidently in the femur joint, identified in Figure 2.

A novel characteristic for legged locomotion is also proposed: resistance. This characteristic describes how much the terrain resists forward movement. This characteristic is best observed in the coxa joints, which must apply a higher torque in response. This differs from specific resistance, a dimensionless quantity essentially analagous to the cost of transport. The terrain characteristic resistance is a dimensioned quantity describing the area under the torque curve.

The terrain characteristic is calculated as the mean average of all the torque data recorded during the relevant section of the gait phase. Noteably, this torque includes an inertial component coupled to the torque required to walk.

3.3 Gait Adaptation

The gait adaptation method presented is an optimisation of the gait parameters $\vec{P}$ (parameters used by the CPG to produce a useful gait) to achieve the most optimal terrain characteristics $\vec{C}$. This method requires models for each of the terrain characteristics and a Dual Extended Kalman Filter (Dual EKF) for the gait adaptation. A useful introduction the EKF is found in [Anderson and Moore, 2012]. It has been used for similar parameter estimation applications in [Wenzel *et al.*, 2006; Loron and Laliberte, 1993].

A general model must be developed for each of the terrain characteristics. This model is designed to accept the gait parameters $\vec{P}$ as inputs and yield some numerical value for the characteristics $\vec{C}$ that can be compared to the measured value.

The platform used for experimental analysis, detailed in Section 4.1, had only two gait parameters that could be altered at run-time: leg height L_H and stride length S_L. Commonly, stride frequency is also alterable.

In order to account for any effect a gait parameter could have on a terrain characteristic, the model should remain as general as possible. The most general model would be some function of n-degree coupled polynomials for each gait parameter. Since these polynomials must be solved at run-time using some estimator on potentially limited processors, this has been approximated as the sum of weighted, decoupled exponentials, generalised in Equation 1.

$$C_n = a_{11}{P_1}^{a_{12}} + a_{21}{P_2}^{a_{22}} + \ldots + a_{n1}{P_n}^{a_{n2}} \tag{1}$$

For the available platform where $\vec{P} = \{L_H, S_L\}$, the terrain characteristic models for resistance and sinkage become:

$$\begin{aligned} \text{Sinkage} &= b_{11}{L_h}^{b_{12}} + b_{21}{S_L}^{b_{22}} + b_3 \\ \text{Resistance} &= c_{11}{L_h}^{c_{12}} + c_{21}{S_L}^{c_{22}} + c_3 \end{aligned}$$

When optimising the model in Equation 1, the optimal gait parameters will result in the lowest terrain characteristic, i.e., the lowest applied torques. This will never be zero unless the motor has failed as the hexapod must also provide a torque to counteract its own weight. On a slippery surface, the slippage characteristic according to the model in Equation 1 will be high when the robot has traction, and low when the robot slips. For a more intuitive characteristic, slippage is modelled as the inverse of Equation 1:

$$\text{Slippage} = \frac{1}{a_{11}{L_h}^{a_{12}} + a_{21}{S_L}^{a_{22}} + a_3}$$

The Dual EKF is an iterative process containing two interdependent EKFs: the model parameter EKF for parameters $\vec{x}_k = \{a_{11}, a_{12}, \ldots\}$, etc. and the gait parameter EKF for parameters $\vec{x}_k = \{L_H, S_L\}$. The full gait adaptation system overview is shown in Figure 4. The goal of the Dual EKF system is to estimate each parameter for the terrain characteristics.

Each EKF consists of 3 major stages. In the first stage, the estimate of the current state is calculated. In the second stage, the input measurements are transformed into the measured state and the error is calculated. In the third stage, the current state estimate is adjusted according to the error and the Kalman gain. The Kalman gain is a quantity representing how trustworthy the measured state is compared with the estimated state.

For both EKFs, the state prediction stage was trivial, since the terrain characteristics were not assumed to change over the length of a single step, i.e.:

$$\begin{aligned} \vec{x}_{k|k-1} &= f(\vec{x}_{k-1|k-1}, \vec{u}_k) \\ &= \vec{x}_{k-1|k-1} \end{aligned}$$

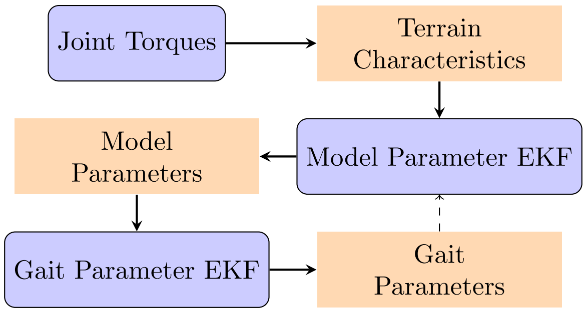


Figure 4: An overview of the Dual EKF gait adaptation system.

This assumption is valid for short steps (i.e., steps made by a small robot) where the step does not cross an obvious terrain boundary such as that between concrete and grass since gradually varying terrain will vary negligibly from step to step.

To obtain the measurement residual for the second stage, the function $h(\vec{x})$, which transforms the predicted state into predicted measurements, must be defined. For the discrete-time EKF, this takes the form of the function $h(\vec{x}_k)$ as in:

$$\vec{y}_k = \vec{z}_k - h(\vec{x}_{k|k-1})$$

where $\vec{z}_k$ is the vector of measured terrain characteristics.

To use in both EKFs, $h(\vec{x}_k)$ must differ in order to incorporate both sets of state vectors. However, once evaluated, the value of $h(\vec{x}_k)$ is the same for both EKFs since it is the set of general functions for the terrain characteristics:

$$h(\vec{x}_{k|k-1}) = \begin{bmatrix} a_1 P_1^{a_2} + a_3 P_2^{a_4} + \ldots + a_{n-1} P_n a_n \\ b_1 P_1^{b_2} + b_3 P_2^{b_4} + \ldots + b_{n-1} P_n b_n \\ \vdots \\ c_1 P_1^{c_2} + c_3 P_2^{c_4} + \ldots + c_{n-1} P_n c_n \end{bmatrix}$$

Using this set of equations to determine either set of parameters analytically is impossible as the system is unobservable due to the chosen model. To deal with this, a non-linear least squares solver using a trust-region-reflective algorithm was implemented. For the model parameter EKF, the error vector $\vec{y}_k$ is minimised. For the gait parameter EKF, the expression is minimised, yielding a $\vec{y}_k$ that serves as a corrective term. Specifically, in this case, $\vec{y}_k$ quantifies the error between the optimal and actual terrain characteristics.

Once $\vec{y}_k$ and the state estimate are known, the updated state estimate can be calculated. For the gait parameter EKF, the new gait parameters stored in $\vec{x}_k$ are implemented in the gait. The equation for this step, when expanding the covariance of the measurement error, is

$$\vec{x}_{k|k} = \vec{x}_{k|k-1} + \mathbf{P}_{k|k-1} \mathbf{H}_k{}^T (\mathbf{H}_k \mathbf{P}_{k|k-1} \mathbf{H}_k{}^T + \mathbf{R}_k)^{-1} \vec{y}_k$$

where $\mathbf{P}_{k|k-1}$ is the covariance of the state estimate, $\mathbf{R}_k$ is the covariance of the zero mean Gaussian white noise in the observation and $\mathbf{H}_k$ is the Jacobian of the function $h(\vec{x}_k)$. The Jacobian is computed at run-time using complex step differentiation [Martins *et al.*, 2003] rather than using first principles because it is more stable at lower step sizes and thus more accurate.

Computing the Kalman gain was not possible analytically as some of the matrices were not invertible. To compute the Kalman gain, the system utilised a Cholesky factorisation [Press, 2007], which had been used previously for this step of the EKF calculation in [Cao, 2008].

4 Experiments

4.1 Platform

The platform used for experimentation was the modified PhantomX hexapod pictured in Figure 1, originally developed by Trossen Robotics [Trossen Robotics, 2014]. The kinematics of this hexapod are described in [Kottege *et al.*, 2015].

Relevant modifications include a camera attached to record the trial and the Leica TS12 [Leica Geosystems, 2016] system to record the ground truth position of the hexapod for the velocity measurement.

The robot's control and movement system were developed using the Robot Operating System (ROS) platform [Quigley *et al.*, 2009], an open source operating system developed specifically for control and communication on robotic platforms. The run-time terrain characterisation and gait adaptation systems were also implemented in ROS.

Some platform-specific limitations include low update rates of the position sensors in the Dynamixel motors at only 20-30 Hz and the microcontroller sometimes dropping packets containing movement commands. Some specific wear in the platform that may affect the results include unevenly worn rubber foot tips and motors past their intended operational life. Communication and power wires may also have affected the locomotion of the robot.

4.2 Terrain Characteristics

To check that the terrain characteristics would properly characterise the terrain, 32 trials across 4 terrains were conducted and compared. It was predicted that walks on concrete at low leg heights, for example, would produce low resistances and moderate slip values; similarly, a walk on mulch at low leg heights and high speeds would produce high resistances and high slip values. Four flat terrains were tested: grass, mulch, concrete, and carpet. Grass and mulch were classed as 'uneven' terrains, whereas concrete and carpet were classed as 'even' terrains. Flat terrains were selected as uneven ground would simply increase or decrease the resistance characteristics.

Each terrain had four trials conducted at constant stride length and varying leg height, and four trials conducted at constant leg height and varying stride length. This data was considered sufficient to confirm the effectiveness of the proposed characteristics to describe the interaction the terrain had with the hexapod if particular trends were identified. These expectations are detailed in Table 1.

Class	**Increased L_H**	**Increased S_L**
Even	Resistance and slip values undergo minor linear increase	Resistance and slip values undergo minor linear increase
Uneven	Negligible difference and/or decrease in resistance, increasing linearly thereafter. Minor linear increase in slip.	Resistance and slip values undergo minor linear increase

Table 1: Expected outcomes of terrain characterisation experiments when compared to lower values

4.3 Gait Adaptation

To test the performance of the Dual EKF, the system was implemented on the hexapod described in Section 4.1.

The bounds for the allowable leg height were

$$20\text{mm} < L_H < 50\text{mm}$$

and for the allowable stride length were:

$$20\text{mm} < S_L < 500\text{mm}$$

This was to avoid legs contacting either the body or each other.

The hexapod adapted its gait on the same four terrains as in Section 4.2: mulch, concrete, carpet and grass.

The performance of the gait adaptation system was quantified by calculating percentage difference in the cost of transport between the beginning of the trial and the adapted gait after it had reached convergence.

The cost of transport c_T was calculated as in [Kottege *et al.*, 2015], reproduced here as Equation 2. When comparing costs of transport within the same trial the mass, gravity, and voltage were all equal. The percentage increase or decrease in the cost of transport over the course of the trial could then be given by the expression in Equation 3 where I is the measured current and v is the measured velocity.

$$\%c_T = \frac{P_{in_2}}{m_2 g_2 v_2} \div \frac{P_{in_1}}{m_1 g_1 v_1} \times 100 \qquad (2)$$

$$\%c_T = \frac{I_{\text{adapted}} \times v_{\text{init}}}{I_{\text{init}} \times v_{\text{adapted}}} \times 100 \qquad (3)$$

5 Results

5.1 Terrain Characterisation

The terrain characteristics were calculated at run-time using real-time data.

The results of the experiments are presented in Table 2. Representative plots are included in Figures 6(a), Figure 6(b), Figure 6(c) and Figure 6(d)

Class	**Increased L_H**	**Increased S_L**
Even	Initial decrease in resistance followed by linear increase. Increase in slip negligible.	Resistance and slip values increase linearly.
Uneven	Initial negligible difference in resistance, increasing linearly thereafter. Linearly increasing slip.	Resistance and slip values increase linearly. Increase in slip at high stride lengths.

Table 2: Observed outcomes of terrain characterisation experiments

The terrain characteristics were able to accurately characterise the interaction between the foot and the terrain:

Uneven Terrains

On high-resistance, high-slip surfaces, such as mulch and grass, the gait phase characteristics reflected their expected values.

Trials with higher leg heights initially showed a decrease in the torque required to move the leg forwards, pictured in Figure 6(a). This is because lifting the leg over the stiffest sections of the terrain (such as the bottoms of the blades of grass and loose soil) eliminates their interaction with the leg's movement. The resistance characteristic increased at high leg heights as the inertia of the vertical movement became coupled to the

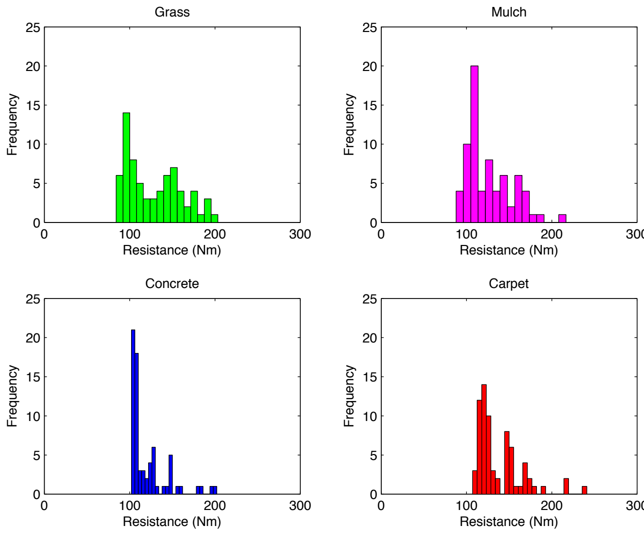


Figure 5: The distribution of resistances across all experimental walks for each terrain.

horizontal movement and the torque required to move the coxa forward increased.

Leg height had little to no recorded impact on slip, as expected.

Increasing the stride length predictably increased the resistance characteristic due to the extra torque required to perform the movement.

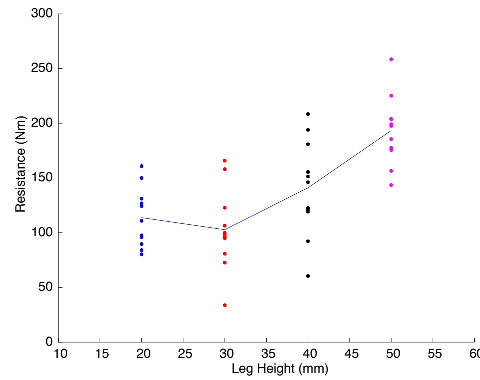
Increasing the stride length, as in Figure 6(c), showed that the terrain became slipperier between stride lengths 300 mm and 400 mm. At this speed, the leg was moving fast enough that it could not find traction and so the average torque during the gait phase section decreased.

As expected, uneven terrains showed much larger variability in their results, pictured in Figure 5. Mulch dominated resistance and sink, but had the highest slip value, implying that the terrain had strong footholds or, much more likely, resisted the leg's backward movement. Grass had a lower resistance on average, which is attributed to the results being skewed by the uneven terrain creating holes where the foot would normally contact the ground: not making contact with the soil reduces the resistance more than movement is inhibited by the grass. The large variances are evidence of why terrain characterisation is an important development in locomotion, as terrain classification does not accurately portray the effect a terrain has on a legged robot.

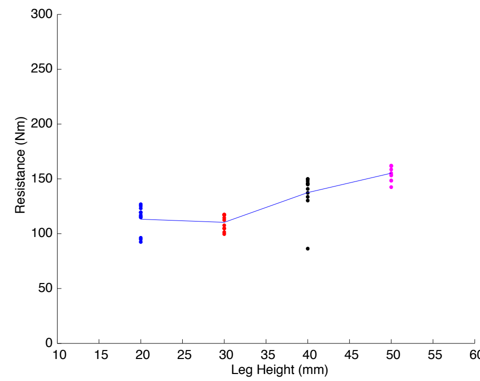
Even Terrains

On low-resistance, low-slip surfaces such as carpet and concrete, the gait phase characteristics reflected that increases in leg height and stride length were not beneficial to efficient movement, as evidenced in Figure 6(b) and Figure 6(d).

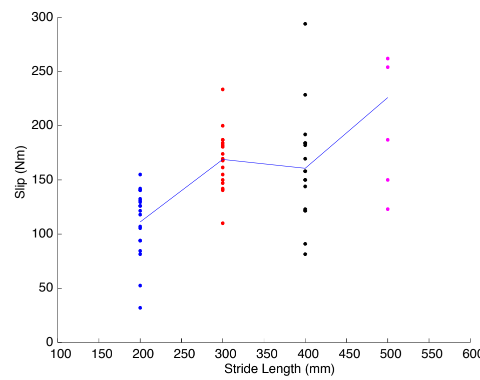
Figure 6(b) also shows that on a perfectly flat surface,



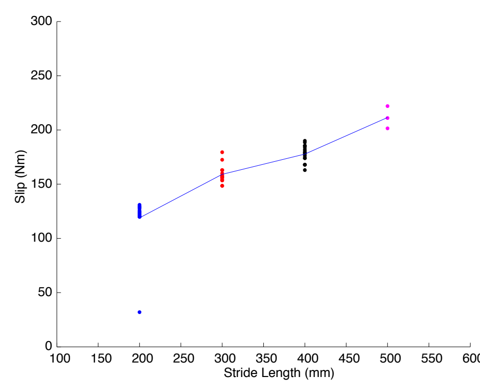
(a) Grass



(b) Concrete



(c) Mulch



(d) Carpet

Figure 6: Resistance and slip on the different terrains at various leg heights (stride length = 300mm) and stride lengths (leg height = 30mm) for the front left leg.

the hexapod stopping the momentum of the leg at low leg heights affected the coxa movement and increased the amount of inertial resistance in that gait phase section, resulting in higher resistance characteristics for higher leg heights.

As expected, changes in leg height did not affect any recorded slip. Minor variations between trials can be attributed to the inertia of the hexapod's movement.

From Figure 5, concrete was the least resistant to movement of any terrain. This would be expected as it is flat, adhesive and hard.

The moderate values for resistance on the carpet terrain are attributed to the leg touching the surface before it had completed its forward motion. The coxa joint would then have to overcome the friction between the foot tip and the carpet, resulting in higher torques and hence higher values of resistance.

Overall, these results are approximately what was expected and so it can be said that they confirm the terrain characteristics' ability to give information to the robot about how its locomotion is being affected.

5.2 Gait Adaptation

Table 3 contains the results of the experimental performance analysis of the gait adaptation system run in real time on the four terrains.

The velocity used for the cost of transport calculation was the average velocity of the hexapod over the period of time the gait parameters were applied. The distance travelled by the hexapod over that time period was calculated using the Leica TS12 station's position sensing as a ground truth estimate.

The trial on the grass terrain showed an increase in the cost of transport. This figure was skewed because both the adapted and initial gaits involved high slippage so small distances were covered during both gaits: the initial velocity on grass was just 29.8% of that on concrete. During the initial gait, the average slip characteristic on the grass terrain was 12.74% lower than that on the concrete terrain, indicating lower torques during this period and hence less traction with the ground.

On the other three terrains, the hexapod was able to properly adapt its gait to achieve a superior cost of transport.

The gait adaptation system was able to improve the cost of transport on three of the four trials, decreasing the cost of transport in the adapted gait to 58.34% of the cost of transport of the initial gait for mulch, 31.1% for carpet, and 33.64% for concrete. On the grass terrain, the hexapod did not correct its gait to account for its slippage, resulting in a very low velocity and an increase in the cost of transport - to 2138.6%.

The adapted leg heights on mulch, concrete and carpet are all as expected, as the leg is not required to be lifted to step over resistive terrain such as grass. For this reason, the leg heights remained at the minimum allowed: 20mm. On the grass terrain, the hexapod was able to determine the leg required lifting, increasing it to 48mm.

The adapted stride lengths all showed increases on low-slip environments, with the concrete terrain trial increasing up to only 410mm while on the mulch and carpet terrains both increased to the maximum stride length of 500mm. The grass terrain trial showed a reduced stride length, only 50mm, which was not enough to step past the particularly slippery blades of grass.

The convergence time for all four terrains was low, with a maximum of 42.92s on the concrete terrain. Were this system to be implemented in the field, it would be able to converge within a reasonable length of time.

The reason that the stride lengths were increased to the maximum for all but one of the trials can be easily determined by comparing the differences in the current draw on each terrain. Even on the grass terrain, almost doubling the leg height only increased the current by 127.1mA. This is a minor increase compared to the 5.77A initial current draw. This particular platform limitation meant that it would always be more efficient to simply maximise the stride length on all terrains.

This Dual EKF system was able to improve the gait to produce the best cost of transport on three out of the four terrains, with the fourth terrain suffering from large amounts of slippage that could not be overcome by increasing the leg height.

6 Conclusions

We presented a novel methodology for a legged robot to characterise the terrain it is traversing in real-time. This was based on proprioceptive torque data acquired during different sections of an alternating tripod gait. The acquired data was mapped on to a time-invariant gait phase to facilitate the characterisation. These characteristics were shown to accurately describe the interface between the legged robot's foot and various terrains. In contrast to terrain classification systems described in the literature, which aims to assign semantic labels to terrain types, the goal of characterising terrain was to derive information from the perspective of robots' locomotion. Furthermore, the characterisation method presented in this paper does not require the system to be trained on multiple terrain types as with traditional classification systems. Therefore, the robot is not limited to operating within previously trained terrain types.

Using general models that related gait parameters to terrain characteristics, a Dual Extended Kalman Filter system was designed. The first EKF would estimate the parameters of the models for each terrain characteristic. The second EKF would then estimate the ideal

Parameter	Mulch	Grass	Carpet	Concrete
Adapted Leg Height	20 mm	48 mm	20 mm	20 mm
Adapted Stride Length	500 mm	50 mm	500 mm	410,mm
$\%c_T$	58.34%	2138.6%	31.1%	33.64%
Initial Current Draw	5.683 A	5.770 A	6.347 A	5.840 A
Adapted Current Draw	5.871 A	5.897 A	6.582 A	5.863 A

Table 3: The results of the gait adaptation system on four terrains.

gait parameters to minimise the model, resulting in lower torques and more ideal locomotion.

The performance of the system was analysed at run time by allowing the hexapod to adapt its gait based on the current terrain characteristics. On carpet, the system was able to improve the efficiency of locomotion: the cost of transport of the adapted gait was just 31.1% of that of the initial gait. On mulch and concrete, the system reduced the cost of transport to 58.34% and 33.64% of the initial gait, respectively. On grass, the system was unable to improve the cost of transport.

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