Using Gait Change for Terrain Sensing by Robots

Sandeep Manjanna and Gregory Dudek
Centre for Intelligent Machines
McGill University
Montreal, Quebec, Canada H3A 2A7
Email: { msandeep , dudek }@cim.mcgill.ca

Philippe Giguere
Department of Computer Science and Software Engineering
University Laval
Quebec City, Quebec, Canada G1K 7P4
Email: philippe.giguere@ift.ulaval.ca

***Abstract*—In this paper we examine the interplay between terrain classification accuracy and gait in a walking robot, and show how changes in walking speed can be used for terrain-dependent walk optimizations, as well as to enhance terrain identification. The details of a walking gait have a great influence on the performance of locomotive systems and their interaction with the terrain. Most legged robots can benefit from adapting their gait (and specifically walk speed) to the particular terrain on which they are walking. To achieve this, the agent should first be capable of identifying the terrain in order to choose the optimal speed. In this work we are interested in analyzing the performance of a legged robot on different terrains and with different gait parameters. We also discuss the effects of gait parameters, such as speed, on the terrain identification computed by a legged robot. We use an unsupervised classification algorithm to classify terrains based on inertial measurement samples and actuator feedback collected over different terrains and operation speeds. We present the effects of speed on the terrain classification in our classification results.**

***Keywords*-legged robots; terrain classification; gait parameters**

I. Introduction

In this paper we consider automated terrain classification by robot vehicles, and how terrain identification can facilitate efficient locomotion. In particular, we consider how changes in the temporal period of a walking gait for a legged robot (based on the Aqua design) can be used to optimize terrain classification, as well as tune the effectiveness of the walk itself in a terrain-depending manner.

Walking robots have the potential to function over a wide range of terrain types such as sand, mud, grass, snow, ice, etc. but different terrains imply different optimal walking behaviours; a phenomenon well known to any person who has had to walk across an ice-covered sidewalk during a Canadian winter. Similarly, terrain-specific gait changes in legged robots are needed to optimize performance. The gait transition from walking to running in humans and other animals has been the subject of extensive prior research. There are several analyses of the transition from walking to running in biological systems as the speed of motion increases [1], [2]. One possible explanation for gait transitions is that the shift to a new mode of locomotion occurs at the mechanical limit of whatever locomotion mode is being used [3]. That is, once the mechanical limit of the legs, walking in particular gait, has been reached due to the speed of motion, the system must switch to a new gait to go any faster. Another explanation proposes that gait transitions occur in order to minimize total metabolic cost, switching mechanism known as an "energetic trigger". The transition can be predicted by observing when the rate of energy expenditure for walking surpasses that for running; this is equivalent to the speed at which running becomes more efficient than walking in terms of energy expenditure per unit distance. Human data indicates this speed to be 2.2-2.3 m/s [4] [5].

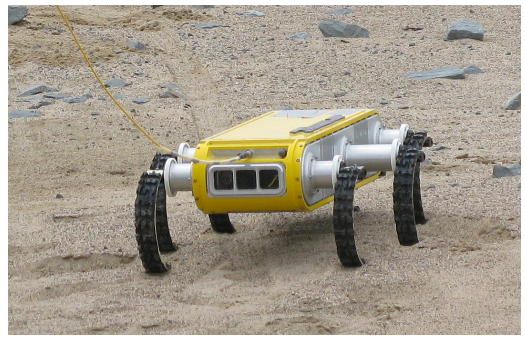

Figure 1. The hexapod Aqua robot, shown equipped with semi-circle legs for land locomotion.

Terrain is one more major factor affecting the decision for the gait changes. The gaits used to walk on different terrains such as grass, sand, snow, ice tend to be different from one another. Stability of the system is greatly affected by gait-depending interactions between the dynamic walker and the terrain on which it is walking. A running gait which would be efficient on grass can fail to maintain stability of the system when used on ice, due to slipping.

In this paper, we concentrate on the performance of the Aqua robot [6] (Figure 1) when operated with varying leg-cycle periods on a range of terrains like dry sand, wet sand, grass and concrete. This vehicle is a hexapod with six compliant legs and a body plan based on that of the RHex robot [7] [8]. We compare the performance of the robot in terms of the energy efficiency per meter of walk. We also compare the terrain sensitivity of the robot at different

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operation speeds. We use an unsupervised machine learning algorithm on the proprioceptive measurements captured over Aqua's walking trials in order to achieve effective terrain identification, following the methodology developed by Giguere et al. [9]. Terrain classification and identification helps in developing terrain models to assess mobility on a given terrain. The classification results for different speeds are compared among each other and the results are also compared with other related works.

II. Related Work

There has been a body of prior work on contact-based terrain classification for both wheeled [10] [11] [12] and legged robots [9] [13] [14] [15], gait transitions in legged robots [16], gait adaptations [17] and explicit tactile sensors [18] [19]. However, substantial work needs to be done in the area of studying the effects of gait-speeds on the performance of the legged robots walking on varied terrains. One of the works by Garcia Bermudez, et al. [13], discusses the maximum velocity achieved by the robot on different terrains. Through our work, we analyze the performance in terms of physical speed and the power efficiency of the robot. Furthermore, a walking robot can optimize its ability to classify the terrain by controlling the way it interacts with the terrain [20]. We have done our investigation on this by comparing the performance of the unsupervised terrain classification [9] over varied speeds of run of the robot on four different terrains.

The study made by Coyle, et al. [21] uses singular value decomposition interpolation (SVDI) to make terrain classification independent of speed. According to this work, the issue with reaction-based terrain classification is the need for large data sets for training the algorithm. Such an approach could be adapted to our system. However, due to our unsupervised learning approach, the cost of using and collecting training data is small. One more similar work is done by DuPont, et al. [22] in which the speed dependency of the terrain classification is eliminated by applying Principal Component Analysis (PCA) on the terrain signatures. Instead, in our work we make use of speed dependencies to increase the classification accuracy of the algorithm.

III. Approach

We would like to start our approach by introducing the Buehler clock which is an essential part of walking gaits of the Aqua robot. The Buehler clock is the computational analog of the central pattern generator [23] in animals. The Buehler clock was originally developed for RHex [7] [24] and is based on a study which shows Cockroach legs are excited by a strongly stereotypical clock reference signal [25]. As the Aqua is based on RHex, it follows a similar pattern for walking. To achieve the tripod-gait, this clock uses a piece-wise linear angle vs. time reference trajectory characterized by four parameters [26]: the total stride or cycle period t_c, the duty factor (the ratio of a single stance period over the cycle period) t_s/t_c, the leg angle swept during stance Φ_s and an angle offset to break symmetry in the gait Φ_0. In our work we change these parameters which in turn affect the velocity of the leg motors. We will refer to these changes as the change in the cycle-frequency f_c as we are affecting the total cycle period t_c of the leg.

As discussed in the introductory section, the optimal gait for an agent can be decided based on many factors: the speed at which it is walking; the energy efficiency of the gait; the mechanical constraint on the legs of the agent; the terrain on which it is walking. We separate the problem into two sub problems as discussed further in this section.

Firstly, the problem is to come up with an optimal cycle frequency - for a particular terrain - at which the robot achieves highest physical speed or operates at power efficient speeds or a trade-off between both. We have investigated this problem by taking the walking trials of robot on four different terrains, like dry sand, wet sand, grass, and concrete floor, with five different cycle-frequencies. We computed the physical speed of the robot by measuring the time from the recorded video and the physical distance between the flag posts. We also recorded the battery current and battery voltage during the runs and computed the power consumed by the robot for every run. Thus we have an estimate of the physical speeds and power consumption of the robot on different terrains when operated with different cycle-frequencies f_c for further analysis of the performance of Aqua.

As a second sub problem, we address the issue related to terrain sensitivity and differentiability. In this work, terrain differentiability is defined as the separation between the terrain classes within a chosen set of features. We collected the inertial measurement samples and the actuator feedback from the walking trials on different terrains as mentioned earlier. The aim is to observe the changes in the terrain differentiability as the cycle-frequency (f_c) changes.

One of the features is the electric current (I_l) flowing in the electric motor of robot legs. A feedback controller maintains the error between the leg angle and the desired trajectory close to zero, by modulating the actuator torque on the legs. This torque at each leg can be modelled as a function of physical features of the terrain, actual leg angle, leg point of contact to the ground and acceleration of the robot. Indeed, this torque is generated by an electrical motor proportional to the electric current flowing in it [14]. Hence leg motor current (I_l) measurements form an important part of the feature set containing the information about the terrain.

Another informative feature is the vertical acceleration of the robot. As the mechanical properties of terrain change, the impact on the robot's dynamics also changes. One of the major impacts in legged robots would be on the

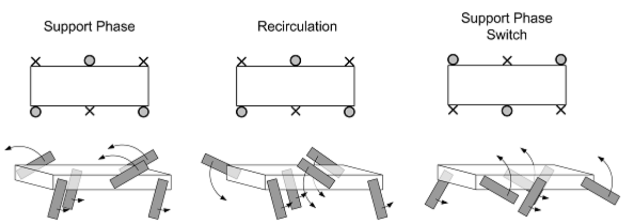

Figure 2. Tripod leg configuration for the walking gait of the AQUA robot. [14]

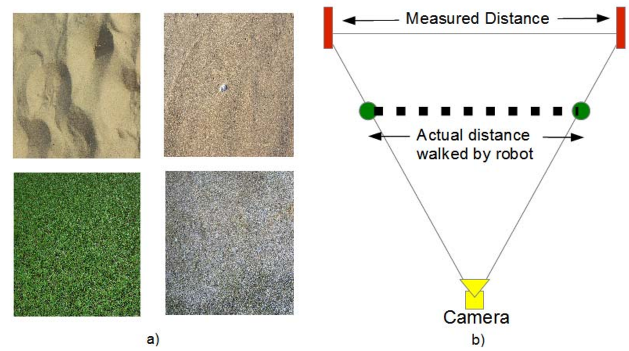

Figure 3. The terrains used for the experiment (dry sand, wet sand, grass, and concrete surface) and the field setup for the experiments.

vertical acceleration as the robot's legs provide different push based on the terrain they are interacting with. Further discussion about the feature set reduction is explained in the experiments section.

We also propose the idea of enhancing the performance of terrain classification by using optimal cycle-frequency for classification. We make use of an unsupervised clustering algorithm [9] which exploits the time-dependency between samples. We use the inertial measurement samples and actuator feedback from the previous experiments to feed the clustering algorithm. We compare the results of the clustering with different cycle-frequencies and with other similar previous works.

IV. Experimental setup

A. Description of the Robot (Aqua 1.0)

The robot used for the experiments (Figure 1) [6] [8] is a hexapod robot that is specifically designed for amphibious locomotion. This robot is based on the RHex [7] [24] robot. There are many kinds of legs designed for the appropriate functionality: semicircle compliant legs for walking, amphibious straight legs for walking and swimming and flippers for underwater swimming. In our experiments for this paper we have used the semicircle legs as in (Figure 1).

B. Robot Gait

The locomotion of the robot on land is achieved by rotating the legs in two groups of three legs, sometimes known as a tripod gait. In this mode of walking, the three legs, two on one side and one on the other side of the robot, form a stable tripod. While one tripod formation is in contact with the ground and propelling the robot forward, the other tripod formation is circulated rapidly around to be ready for the next support phase [14] (Figure 2). This quick alternation of support coupled with the compliant nature of the legs results in a complex dynamic interaction between the robot and the ground. This tripod gait is used for the experiments mentioned in this paper.

C. Data collection

The experiment trials were performed on four different terrain types with five cycle-frequencies f_c evaluated on each terrain. The f_c of the Buehler clock is controlled by changing the input speed levels in the graphical interface of Aqua. Five different f_c are achieved by changing the input speed control setting to five levels, like 0.1, 0.2, 0.4, 0.6 and 0.8, on the graphical speed bar of the interface. For each speed control setting and every terrain, five trials are taken.

The Collected data is a mixture of many sensor measurements as mentioned below. The Relative leg rotations are measured using optical encoders attached to the motor shafts and a MSI-P400 quadrature decoder card is used to decode the signals from light receivers. Leg motor electrical currents are estimated using carefully calibrated motor models [27]. These models compute an electrical current estimate based on the physical parameters of the motors, the voltage command to the motors and their angular velocities. The robot is equipped with a 3-axis Inertial Measurement Unit (3DM-GX1TM), which possesses 3 Micro-Electro-Mechanical Systems (MEMS) acceleration sensors, 3 MEMS rate gyroscopes and 3 magnetometers. The accelerometers measure the acceleration of the robot's body, in m/s^2. The rate gyroscopes return the angular velocity of the robot's body in rad/s. The data is collected from these sensors at a rate of 20 Hz, i.e. 20 readings of sensor data per second.

The video of all the trials was recorded from a fixed distance as explained in the next subsection. This video is used to compute the time taken by the robot to cover the experimental path distance. This time is more accurate than the stopwatch timing and it is used in computing the physical speed of robot.

D. Terrains and the field setup

The experiments were conducted on four kinds of terrains (Figure 3a), namely dry sand, wet sand, grass and concrete surface. The setup as seen in Figure 3b was used on these terrains and Aqua was made to walk from start point till end point.

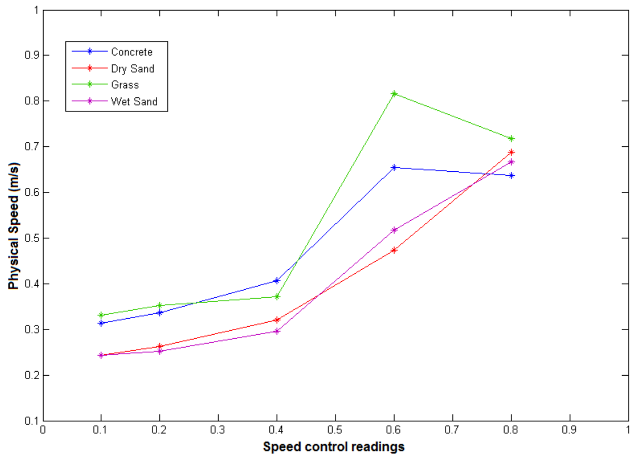

Figure 4. Physical speed of robot plotted against the speed control readings of the leg rotation. The plot shows the variation found over different terrains.

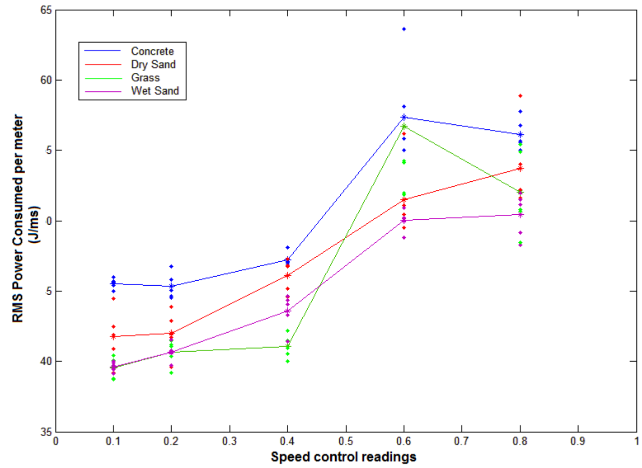

Figure 5. Root mean square of the power consumed per a meter walk of the robot. The plot shows the errors in the readings over five trials for each speed and terrain.

V. Experimental Results and Observations

A. Performance at varying speeds

This experiment was done to see the effect of speed (f_c) on the performance of Aqua robot. The performance is measured in terms of physical speed and power consumed per meter walk. In Figure 4, we can see that the physical speed of the robot increases with cycle-frequency for soft granular terrains like dry and wet sand. However, the physical speed of the robot on hard terrains like grass and concrete surface starts to decrease at the higher speed control setting of 0.8. We suspect that the robot legs start to slip from the surface of terrain when rotated at very high speeds on hard terrains. On soft terrains, the granularity of the terrain gives grip to the legs and helps the robot achieve higher physical speeds. Thus, to achieve higher physical speeds on hard terrains, the speed control setting of the robot should be capped to the range 0.6 to 0.7. To achieve the same on soft granular terrains the robot needs to operate at its highest cycle-frequency of the leg motors. These results thus clearly show that the type of terrain has a strong influence on the velocity of the robot, for fixed gait parameters.

The plot (Figure 5) shows the variation of power consumed per unit distance walk of the robot with varying cycle-frequencies. From the results it is evident that the robot reacts differently to hard and soft granular terrains. There is a trade-off between the cycle-frequency at which the robot consumes less power yet achieves acceptable physical speeds. For example, on wet sand the robot can operate at high cycle-frequency of 0.8 achieving highest physical speed, still maintaining less power consumption compared to other terrains. However on dry sand it is very power expensive to operate at high cycle-frequency.

B. Terrain differentiability

We have analyzed the effects of cycle-frequencies (operating speeds) on the differentiability of the terrain classes. We created a feature set as explained in the section 2 by considering the leg motor currents (I_l) and vertical accelerations (A_z) as these features of robot are most affected by physical interaction with the terrains. The dimensionality of the feature set was reduced by sampling the data at one particular angle of the leg rotation cycle, at which the separation between the terrain classes was the highest [28]. In Figure 6, the features I_l and A_z are plotted as a function of leg angle. The plot also shows the optimal angle (1.25 radians) at which the classes are well separated. The optimal angle was computed by considering the angle at which the average distance between the classes was Maximum. Then the data was sampled at leg angle of 1.25 radians and used for further results.

The results in Figure 7 show the data samples from different terrains sampled at the leg angle of 1.25 radians. The data samples were collected over all 5 speed control settings (i.e. f_c of leg rotation). It can be inferred from the results that the separation between the classes varies as the speed control setting changes from 0.1 through 0.8. Moreover, this class separation is terrain-dependant. For example, the terrains grass and dry sand are well separated at the speed control setting of 0.1, but not separated at the speed of 0.8. Similar observations can be made for different pairs of terrains. This emphasizes the impact of terrains on the robot's dynamics.

These results can be used to analyze how difficult it is to classify the classes at different f_c. They can also be used to verify the terrain identified by the robot. For example, if the robot identifies the terrain to be concrete while walking with

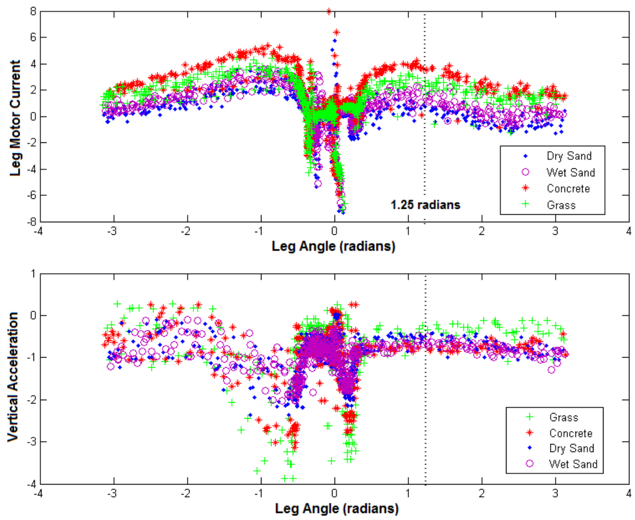

Figure 6. Leg motor current and Vertical acceleration (A_z) plotted as a function of Leg angle. The plot also shows the angle (1.25 radians) at which the data sets collected from different terrains are well classifiable.

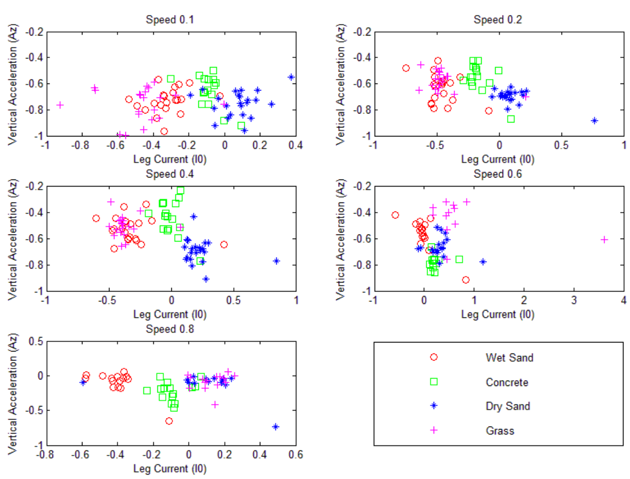

Figure 7. Distribution of sensor measurements in feature space (motor current I_l, vertical acceleration A_z) sampled at leg angle 1.25 rad, with changes in the speeds of operation (f_c of the leg rotation).. The data shows four terrain classes.

a speed control setting of 0.1, it can switch the speed control setting to 0.8 and re-run the identification to be sure of the terrain detected. Once the terrain is verified, the robot can also choose a f_c at which that particular terrain is isolated and verify which all terrains the robot is not on. Thus, these results are very useful in real-time gait adaptation for the terrain qualities.

C. Terrain Classification and the cycle-frequency

We have already identified how the changes in cycle frequency have an impact on the way the terrain classes are distributed in the feature space. To assess the effect of cycle-frequency on the terrain classification, we classified the terrain data with an unsupervised terrain classification algorithm proposed by Giguere et al [9].

1) Algorithm and Data sampling: The algorithm used is an unsupervised clustering of unlabelled samples of the sensor data. These samples represent sequences of consecutive measurement from the robot as it traverses the terrains. Since the samples are generated through a physical system interacting with a continuous or piece-wise continuous terrain, time-dependency will be present between consecutive samples. The clustering algorithm [9] explicitly exploits this time-dependency. It is a single-stage batch method, eliminating the need for a moving time-window.

The algorithm works by minimizing a cost function which minimizes the variation of classifier posterior probabilities over time, while simultaneously maintaining a wide distribution of posterior probabilities. The aim of the algorithm is to search for the parameters $\vec{\theta}$ that minimizes the following cost function,

$$\arg\min_{\vec{\theta}} \sum_{i=1}^{N_c} \frac{\sum_{t=1}^{T-1} (p(c_i|\vec{x_{t+1}}, \vec{\theta}) - p(c_i|\vec{x_t}, \vec{\theta}))^2}{var(p(c_i|\vec{X}, \vec{\theta}))^2}$$

The dataset needed for the algorithm are,

- A sample set $\vec{X}$ of T time-samples of feature vectors $\vec{x_i}$, generated by a Markovian process with N_c (No. of Classes) states.
- A classifier with parameters $\vec{\theta}$ used to estimate the probability $P(c_i|\vec{x_t}, \vec{\theta})$, that the sample belongs to class $c_i \subset C$.
- A set of parameters $\vec{\theta}$ that is able to classify the data set $\vec{X}$ reasonably well.

The classifier input $\vec{x_t}$ used for this work was collected by sampling 13 sensors - comprising of 3 accelerometers, 3 rate gyroscopes, 1 leg angle encoder and 6 motor current estimators - at a rate of 30 samples per one cycle of the leg. Thus each feature vector, $\vec{x_t}$ is of size 13x30. The dimensionality of the dataset was reduced by applying Principal Component Analysis and only the top $N_f = 5$ number of features were selected for the classification. The advantage of this algorithm is that it can be evaluated with three different kinds of classifiers based on the knowledge about the class distributions. For this work we have used the k-Nearest Neighbors (kNN) classifier with this cost function.

2) Results: The results indicate that there are specific cycles-frequencies or speed control settings at which the classification between different sets of terrains becomes more accurate. As illustrated in Figure 8, the speed control setting of 0.4 is optimal for most of pairs of terrains. However, for dry sand and grass, a speed control setting of 0.8 gives better classification success rates and for Grass and Concrete, a speed control setting of 0.2 gives better classification success rates. The classifier performs better when the speed factor is involved. The success rate for two

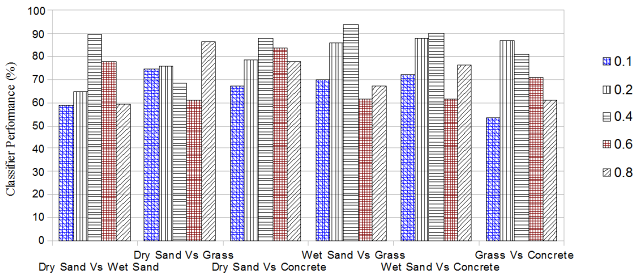

Figure 8. Plot to show the variation in the performance of the classifier with the cycle-frequency. It shows a comparison between different pairs of terrains.

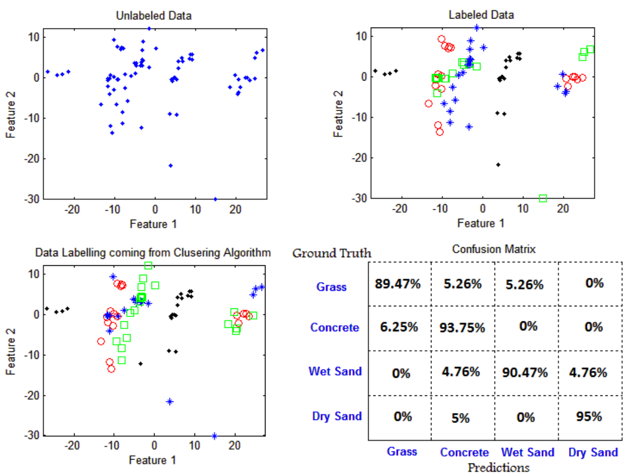

Figure 9. Results of the classification algorithm run on the data set collected at a speed (C_f) of 0.4 and N_f=5 (PCA features) selected from the data. Also shows the confusion matrix of the classification.

class classifier is estimated around 90% at the optimal speed. This is more efficient than the success rate of 73.75% in [9].

The previous results suggest that 0.4 speed control setting is optimal for classification of most of the terrains. Hence, we classified the data from four different terrains collected at the speed control setting of 0.4. Top 5 (N_f) PCA features from the data were used. We see from Figure 9 that the performance is very good and comparable to the similar experiments done in [13] with an overall success rate of 92.11%. But the advantage here is the use of unsupervised algorithm on unlabelled data and still being able to produce similar results. There was training with just unlabelled data and the feature set used is also very small. Thus the results are very promising and push us to do more work on similar lines in future.

VI. CONCLUSION

The main aim of this work was to quantitatively measure the effects that gait parameters can have on the performance of a robot when it walks on different terrains. We also evaluated the performance of the terrain classification when operated at different cycle-frequencies. Some of our results suggest that the optimal speed of leg rotation for energy consumption is tied to the terrain type. Thus, by controlling the cycle-frequency one can achieve a trade-off between the physical speed and power consumption of the robot.

We also demonstrated that the terrain identification sensitivity of the robot, and thus the error margin of the classifier, differs when it walks with different cycle-frequencies. This implied that active gait selection should improve classification accuracy. In fact, we observed a significant increase in efficiency of the terrain classification algorithm by varying the cycle-frequency of the leg rotation. While this notion is consistent with human experience, we believe this is the first time this phenomenon has been reported or quantified in a robotics context.

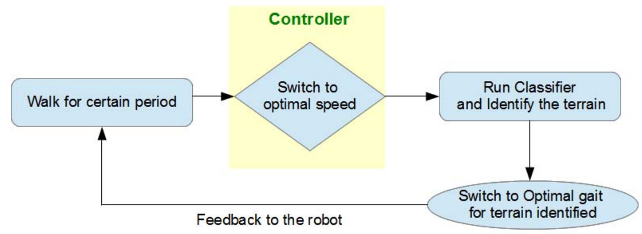

Figure 10. Gait-switch system - A complete real-time gait adaptation system with a controller to choose optimal speed of walk before the terrain classification is invoked.

VII. FUTURE WORK

The classification problem is highly dependent on the set of features selected. We would like to experiment with the larger feature sets and evaluate the obtained results. We also plan to extend and generalize our results to a more diverse set of terrain types, more rugged non-flat terrains, like gravel, rocky paths, etc.

In the near future, we plan to build a gait-switching system (Figure 10) for automated real-time gait adaptation in Aqua [6] based on real-time terrain classification. Our current results suggest that gait-alterations can be used to enhance both walking efficiency as well as identification itself.

The increased performance of the classifier with varied cycle-frequencies suggests that the accuracy of the gait-switch system can be improved by including a speed controller. This controller would switch the robot to an optimal speed for the classification, so that the classifier predicts the terrain more accurately. We also plan to build the controller to be decision tree based; so that it could choose an optimal speed from a set of speeds. Decision could be made based on some conditional queries about the current terrain the robot is walking on and the probability with which the next terrain is predicted.

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