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The effect of motor action and different sensory modalities on terrain classification in a quadruped robot running with multiple gaits

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HIGHLIGHTS

- Preconditioning on gait used boosts terrain discrimination in a legged robot.
- Specific gaits are particularly suited for terrain perception.
- Inertial, tactile, and proprioceptive sensors are a robust terrain sensing set.
- Encoders in passive compliant joints performed best from the sensory set.

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ABSTRACT

Discriminating or classifying different terrains is an important ability for every autonomous mobile robot. A variety of sensors, preprocessing techniques, and algorithms in different robots were applied. However, little attention was paid to the way sensory data was generated and to the contribution of different sensory modalities. In this work, a quadruped robot traversing different grounds using a variety of gaits is used, equipped with a collection of proprioceptive (encoders on active, and passive compliant joints), inertial, and foot pressure sensors. The effect of different gaits on classification performance is assessed and it is demonstrated that separate terrain classifiers for each motor program should be employed. Furthermore, poor performance of randomly generated motor commands confirms the importance of coordinated behavior on sensory information structuring. The collection of sensors sensitive to active, "tactile", terrain exploration proved effective. Among the individual modalities, encoders on passive compliant joints delivered best results.

1. Introduction

The movement of every mobile robot, both legged and wheeled, is strongly affected by the interaction with the environment it is traversing. Successful perception of the terrain is a key ability that impacts the decision-making of the robot – whether to enter a particular area or which speed or gait to choose – and hence its performance in different situations. Furthermore, being able to perceive the terrain properties can be an important precondition for successful navigation performed by the robot (see e.g., [1]). Terrain can be discriminated in a supervised manner – matching the environment with predefined categories like tar or sand – or in an unsupervised manner. The former is known as *robotic terrain classification* (e.g., [2]). If the terrain classes are not available to the robot, different unsupervised methods can be employed to discover the different terrain types (e.g., [3]). A related notion has been put forth by Ojeda et al. [4]: terrain characterization, which aims at determining key parameters of the terrain that are relevant to the traversability by the robot. We will use *terrain discrimination* to encompass all of the above.

A large variety of methods is applied to terrain discrimination: these include different sensors, different methods to preprocess them, and finally different algorithms to discriminate between the terrains. Often, sensors that perceive at a distance like cameras,

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laser scanners or radars are used, sometimes supplemented by inertial sensors. Sensors that directly perceive the robot's physical interaction with the environment, like tactile sensors, or proprioceptive sensors, which reflect how the robot's body negotiates different grounds, are used less often. Furthermore, the type of motor action the robot is using while performing terrain discrimination is typically not considered. In this work, we investigate the possibilities of distinguishing terrain types using a collection of inertial, tactile and proprioceptive sensors and we specifically address the consequences of using different motor actions. We choose a platform with significantly different "motor regimes": a quadruped robot running with multiple gaits. In order to lend more credence to this investigation, we employ two different classification algorithms (naïve Bayes and Support Vector Machines—SVM) and a large pool of time and frequency domain features.

This article is structured as follows. Section 2 covers related work on this topic. In Section 3, the experimental setup and methods for data collection, feature computation and classification are sketched. Section 4 provides a mathematical formulation of the problem. In Section 5, results and analysis are presented. Finally, Section 6 concludes the paper with a discussion and directions of future research.

2. Related work

Typical examples of robot terrain classification involve wheeled platforms equipped with a camera, accompanied by a vibration sensor, like an accelerometer [5], or a microphone in the case of the Mars rovers [6]. Giguere and Dudek [7] introduced a metallic rod with an accelerometer dragged behind the robot; Ojeda et al. [4] experimented with a richer collection of sensors. The motor action of the robot during the classification task is typically not considered; occasionally, different speeds [8] or speed and load were considered [9].

There is much less work on legged robots. Filitchkin and Byl [10] used a compact camera mounted on the Little Dog robot for terrain classification; Belter and Skrzypczyński [11] used a laser scanner on a hexapod to map the terrain around the robot and choose footholds. However, legged robots are particularly suited for tactile exploration of the terrain being traversed. Hoepflinger et al. [12] estimated surface properties from joint motor currents and force sensing resistors while the robot's leg was probing the surface; Kim et al. [13] varied the gaits in a monopod platform and used ground reaction force and torque sensing for classification. Giguere et al. [3], Garcia Bermudez et al. [14], and Manjanna et al. [15] used hexapod robots with semi-circular legs and combined several sensory modalities: inertial sensors, encoders, and back-EMF sensors or motor current estimators. Regarding the effect of the motor signal, the effect of gait frequency on classification performance was studied in [14,15]. Finally, Larson et al. [16] used a simulated robot and a limb/terrain interaction model to evolve gaits that facilitate terrain classification based on gait bounce—estimation of the loping motion of the robot as it locomotes.

A variety of features is used to preprocess raw sensory streams. Leaving visual features aside, the most common is the combination of statistical moments (mean, variance, skewness, kurtosis etc.) in the time domain with frequency domain features [7,3,17,12]. Some authors rely on the frequency domain only [18,9,4]. Various algorithms are employed to perform the classification: Support Vector Machines (SVM) [8,5,6,13], other physical probabilistic models [19], neural networks [9,20,17,21,4], linear discriminant analysis [22,23], principal component analysis (PCA) [9,24,13], or adaptive Bayesian filtering [25]. In [17,3] comparison of the traditional classification methods is provided, furthermore, in [7] both supervised and unsupervised techniques are successfully applied showing that PCA can be used to reduce the data dimensionality without impacting on the classification results.

In this work, we will employ two standard classification algorithms (naïve Bayes and SVM) and a feature set comprising standard time and frequency domain features. The focus, however, will be on two aspects that have been largely overlooked so far: the effect of motor action and the collective as well as individual performance of inertial, tactile, and joint angle sensors to discriminate the properties of different terrains. Our work has a similar flavor to some of the work in terrain classification in legged robots that we reviewed above [14,3,12,15], but goes further in that very different dynamic locomotion patterns – gaits – are considered. We follow up on previous work on the Puppy quadruped robot [20,26]. In [20], a dataset comprising three gaits was used and the performance of different sensor sets was addressed, however, the data was collapsed across the gaits. Preconditioning on the gaits was first used in [26]; in this work, it is extended in the following ways: (i) A new, much more comprehensive feature set, and an additional classifier are introduced; (ii) A more elaborate analysis is performed and specific effects of individual gaits are studied; (iii) The effect of different sensory modalities is analyzed; (iv) The interplay of the four different factors impacting on the classification performance (gaits, sensory modalities, classifier, features) is investigated; (v) An additional dataset is added to study the contribution of additional sensors and the effect of random motor signals on classification.

3. Experimental setup

3.1. Robots and ground materials

The basic experimental setup is identical to [26]—the same dataset was used in this work. We recapitulate it here briefly for the reader's convenience. The Puppy robot (see Fig. 1 left) has four identical legs with two revolute joints per leg: the hip driven by servomotors and the knee passive compliant—with a spring attached across it. Four potentiometers measured the joint angles on the passive knee joints and four pressure sensors recorded forces at the robot's feet. Linear accelerations were measured by an onboard 3-axis accelerometer. All sensory channels were sampled at 50 Hz.

Five sets of position control commands for the servomotors were prepared, resulting in 5 distinct gaits (bound forwards, bound left/right, crawl, trot backwards). The target position trajectory for every motor was a sine wave at 1 Hz with a specific amplitude, offset, and phase lag. Gaits were chosen randomly and exercised in 2-second-intervals during which the sensory data were collected, forming what we call epochs. At the end of each epoch the robot could change the gait. There were two locomotion periods in every epoch. For analysis, only data from the second period is used; the first one – immediately after the gait transition – is discarded.

A small wall-enclosed arena of 2×1 m was prepared and subsequently covered with four different ground substrates—data was collected on each of them in turn. The materials were plastic foil, cardboard, Styrofoam and rubber. They differed in friction[1] and also in structure: cardboard and rubber had ridges that – especially in the case of cardboard – rendered the terrain non-flat relative to the robot size (about 1 cm high ridges vs. 6 cm leg length). When the robot was approaching the wall of the arena, this was detected by an infra-red distance sensor and the "trot back" gait was triggered until a safe distance was established and random gait selection resumed. In what follows, we will refer to the dataset coming from this robot as "Real robot".

[1] We estimated static friction coefficients between the ground materials and robot's feet by putting a block covered with the same adhesive skin as on the robot's feet on inclined planes covered with the different ground materials. As the adhesive skin has asymmetrical properties, two values were obtained for each material. The low/high values were: plastic foil: 0.39/0.39, cardboard: 0.64/1.10, Styrofoam: 0.74/1.06, rubber: 0.76/0.91.