The quadruped ALoF and a step towards real world haptic terrain classification

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ABSTRACT
The intention of this paper is twofold. It first describes the robotic platform ALoF and its control software framework which was designed for autonomous locomotion in rough terrain. The robot has a very large range of leg motion to actively explore its surroundings through haptic interaction and to increase its locomotion capabilities. The platform is robust enough to carry adequate sensors to perceive the surrounding environment. As a step towards reliable terrain classification for legged robots, we are additionally presenting a novel method based on haptic feedback. The method has been evaluated on a simplified ALoF leg, employed in a test setup. Eleven different samples of natural terrains have been classified in experiments. Features, extracted primarily from contact force and motor current measurements, were used for training and prediction by a multiclass AdaBoost machine learning algorithm. About 87% of the real terrain samples have been classified correctly.

1. INTRODUCTION

The advantages of legs, in comparison to other principles of locomotion, are in large part confined to difficult and rough terrain in which other systems might fail completely. For most other scenarios, alternative systems generally show a superior performance, especially with respect to locomotion speed and energy consumption – the two factors that largely limit the operational range of mobile robots and hence their physical autonomy. While fundamental research on the principles of legged locomotion is highly desirable to lessen these disadvantages, the ultimate goal of legged locomotion systems must be their application in rough and highly unstructured terrains. Recent research results, for example within the scope of the DARPA learning locomotion challenge [1, 2], have shown impressively, that this is possible with the current state of the art. Yet, by using external sensors and a pre-generated digital terrain model, the robots in this project were at all times made aware of their exact state and the detailed shape and properties of the surrounding environment. This reduced the locomotion task to a problem of motion planning and execution. In any given real application, however, such knowledge is not readily available. It must be collected by the robot itself, thereby generating an additional task for perception. The representation of the environment that is generated in this process must be tailored to the specific needs of the robot. For a locomotion task, this means that the robot has to obtain information which is relevant for a proper foothold selection.

The contribution towards autonomous mobility in unstructured and unknown environment that is presented in this manuscript goes in two directions: On the one hand, we introduce the newly developed research platform ALoF (Autonomous Locomotion on Four legs) that is designed to aid research on perception for legged locomotion and foster the creation on systems that are able to navigate fully autonomously through rough terrain. On the other hand, we describe the implementation and the evaluation of a method for haptic terrain classification which will allow ALoF to determine the properties of the ground it is standing on. In this study, which was performed in a test bed with a single ALoF leg, we specifically focused on natural terrain samples, ranging from solid surfaces such as for example concrete or ice to loose ground as for example sand.

2. QUADRUPED SYSTEM DESCRIPTION

Our robot (Figure 1) is a four legged quadruped with a total weight of about 15 Kg and linear dimensions in the range of half a meter. This means the platform is small enough to be handled by one person alone, yet able to carry larger and more sophisticated sensors, as for example stereo cameras, laser range finders, and the like. Each of the legs has three degrees of freedom, allowing for hip abduction/adduction, hip flexion/extension, as well as knee flexion/extension. The three joints are set up in a ‘mammalian’ configuration, with the two knees facing each other, which generates more symmetrical ground contact forces. The feet are not actuated. We limited ourselves to the minimal number of degrees of freedom, to keep the complexity low and thus increase the robustness, modularity, and ease of maintenance of the system.
A bevel gear drive at the knee allows for a large motion of the knee joint, which can flex -160° and extend 90° from a fully outstretched position. The two hip joints are actuated by a differential drive system that allows a 360° rotation of the leg about the flexion/extension-axis (the actual range of motion is solely limited by the need for a power and signal connection to the knee-joint). The main body was specifically designed to impede hip abduction/adduction as little as possible. This motion can therefore reach ± 45° from vertically downwards (Figure 1, right hand side). Such a large range of motion allows for a greater variation of foot placement and hence provides the robot with the necessary choices for challenging planning tasks. It facilitates haptic exploration of the terrain, and enables the execution of alternative gait patterns and recovery maneuvers. This includes, for example, the task to stand up after falling down, which adds an intrinsic robustness component to the locomotion task.

To be able to actually exploit this large range of motion, we equipped all joints with very strong actuators. 12 DC motors (Maxon RE25, 24V) with a gear-box ratio of 79:1, (which is additionally amplified by the bevel-gears) generate enough torque, such that the legs are able to lift four times the weight of the robot main body when standing up from the ground. 12 individual servo controllers connected by a CAN-bus take care of low-level velocity/position control and are controlled by a NI single-board RIO, which combines a FPGA-controller and a real-time processor for the different layers of data acquisition, control, and safety functionalities. This controller is connected to a host-computer via a UDP/IP connection. High level control and energy-supply are provided off-board to save weight and reduce complexity. The detailed hardware characteristics are listed in Table 1.

![Figure 1. Left side: The ALoF robot additionally equipped with pan-tilt cameras, lights and a dust-protection cover. Right side: A differential drive at the hip, bevel gears at the knee, and the compact design of the main body allow a very large range of motion for all legs.](image)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
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<tbody>
<tr>
<td>Overall Length [mm]</td>
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<tr>
<td>Typical Height [mm]</td>
<td>400</td>
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<td>Overall Width [mm]</td>
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<tr>
<td>Main Body Mass [Kg]</td>
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<tr>
<td>Torque Knee, (continuous/peak) [Nm]</td>
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<td>Torque Hip, (continuous/peak) [Nm]</td>
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<table>
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<th>Parameter (cont.)</th>
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<td>Spacing between hip joints (longitudinal) [mm]</td>
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<td>Spacing between hip joints (lateral) [mm]</td>
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<td>Length of Shank Segment [mm]</td>
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<td>Foot diameter [mm]</td>
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<tr>
<td>Maximum peak load for standing up [N]</td>
<td>400</td>
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<tr>
<td>Range of motion for hip flexion/extension [°]</td>
<td>±180</td>
</tr>
<tr>
<td>Range of motion for knee flexion/extension [°]</td>
<td>+90/-160</td>
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Figure 2 depicts a schematic of the hardware/software configuration of the robot. The high level control is based on the Simulation and Real-Time Control - Software framework developed by the University of Southern California [3]. This software includes modules for robot control, simulation, and visualization. A task control module contains the higher level control laws, e.g. for trajectory planning, which are executed in the motor control module that holds the low level control to generate the joint motor commands. Currently, the control loops on the host computer and on the on board computer are executed at a rate of 250 Hz.

A separate GUI has been implemented to command the robot state machine for additional supervision of the robot. It visualizes the actual state and the errors reported by the robot. Communication between host and on board computer is managed over an interface that handles the UDP message transfer. The lowest control level including the motor and sensor communication and evaluation as well as all safety critical operations are running on the onboard NI single-board RIO where real time operation can be guaranteed.

![Graphical User Interface to control the statemachine of the robot](image)

**Host PC**

**SL – Simulation and Real-Time-Control**

- **Task Control** (Trajectory planning ...)
- **Motor Control** (Inverse Kinematics, Inverse Dynamics)

**Communication Interface**

**Robot**

- On board computer (NI Single Board RIO)
- Actuators, Sensors

Figure 2. Simplified schematics of the software / hardware configuration of the ALoF Robot

### 3. REAL WORLD HAPTIC TERRAIN CLASSIFICATION

Successful legged locomotion in rough and highly unstructured terrain mainly depends to a large extend on the stability of the robot, i.e. its ability to move without falling or tipping over. Existing stability measures can be roughly classified as static or dynamic. Static criteria (e.g. Center of Mass projection method, CoM, [4]) completely ignore the robots motion while dynamic criteria such as Center Of Pressure method (CoP, [5]) or the Zero Moment Point method (ZMP, [6]) also consider the current acceleration of the robot. Nevertheless, most of these criteria are solely based on a simplified terrain model, neglecting terrain material properties and small scale geometry around the foot hold. However, these properties will have a very big influence on the actual stability of a legged robot, as they determine the risk of slipping and sliding and the overall reliability of a stance. In order to be able to increase the robustness of rough terrain locomotion under static and dynamic considerations, a robot must be made aware of the detailed properties of the terrain it is standing on. The necessary terrain models could be built by discretely separating the terrain in classes, which can then be used to estimate the quality of a foothold. This issue of terrain classification has been exhaustively addressed for wheeled [7-10] or tracked locomotion [11], but has drawn very little attention in the area of legged locomotion. Along the lines of our first step towards terrain classification for legged robots using artificial terrain samples [12], we present in this paper an extended approach to terrain classification for a selected set natural terrain samples.
In an experimental setup for haptic terrain classification, a single leg was separated from the ALoF robot and mounted in a test bed (Figure 3), which contained a sample holder with different terrain samples. A predefined measurement protocol determined the motion of the leg and data from the knee joint actuator, from the passive hip joint, and from the force sensing device was recorded during the motion. Based on these recordings, features were extracted and used by a machine learning algorithm for supervised terrain classification. The software and hardware components developed for those experiments are described in detail below.

3.1 **LEG ACTUATION**

By blocking hip adduction/abduction the originally three degrees of freedom of the robotic leg were reduced to two, of which only the knee joint was actuated by an electric DC-motor. Since the rotational axis of the passive and of the active joint were parallel, the motion of the foot was limited to a circular disc and constrained by the surface of the sample. Due to the passive hip joint connecting the leg with the fixed base, the normal ground contact force was solely generated by the weight of the leg.

3.2 **FORCE SENSING DEVICE**

To capture ground contact forces, a force sensing element was developed and mounted into the shank of the leg. The force sensing element consisted of three individual force sensing resistors uniformly distributed around the leg axis. This setup allowed measuring the force along the shank axis as well as the two bending moments in the cutting plane, therefore deducing the normal and the tangential force at the ground contact point. The upper and the lower part of the force sensing unit were connected with a fixed bolt that exhibited a constant pre-compression force onto the sensor layer and additionally enabled the measurement of tensional forces. As force sensing elements, force sensing resistors (Interlink Electronics FSR-400) have been incorporated. While these sensors are very cheap and readily available, they have considerable drawbacks: They are not suited for high precision measurements and show a substantial hysteresis which makes them ill suited for dynamic measurements. On the other hand, they are very inexpensive and easy to use and their performance is appropriate for tasks as collision detection or terrain classification in the field of walking robots.

The output signal of the force sensing device is filtered, amplified and sampled with a sampling frequency of 50 Hz by a microprocessor (Microchip DSPIC33FJXMC710) and sent via UART interface to a personal computer. The PID motor control of the knee actuator was performed on a standard motor controller (Maxon EPOS 24/5) that was connected via CAN-bus to the PC. The bus was used to exchange motor control commands and motor level sensor data.
3.3 TERRAIN SAMPLES

For the terrain classification, flat terrains with different natural terrain properties were mounted onto the testbed. Experiments were performed with eleven different terrain types: standard sand, Martian soil simulant (DLR), gravel (crushed rocks and round gravel with each three different ranges of particle sizes) as examples of soft surfaces and finally concrete (made of Jura Portland cement, sand and water), asphalt and ice as examples of solid surfaces (Figure 4).

![Terrain samples](image)

Figure 4. Picture of the terrain samples used to evaluate the classification method. They are divided into solid terrain materials such as concrete (a), ice (b) and asphalt (c), and compliant terrain such as martian soil simulant (d), sand (e), crushed sand (< 2 mm) (f), split (< 4 mm) (g), split (4-8 mm) (h), split (8-16 mm) (i), round gravel (4-8 mm) (j), round gravel (8-16 mm) (k).

3.4 MEASUREMENT CYCLE

To obtain sensor data for terrain classification the knee joint was actively rotated by 10°. The motion allowed recording the effects caused by the transition between static and dynamic friction and therefore estimating the friction coefficient of the surface material. A sample plot of the measured and pre-processed force sensor data in the time domain and of the corresponding measured knee angle and knee joint motor current is presented in Figure 5.

![Measurement cycle](image)

Figure 5. Plot of a sample measurement of the knee angle, the motor current (a) and the pre-processed force sensor signal (b).


3.5 Classification

After the execution of a measurement cycle, the collected sensor data was pre-processed and then used for feature generation. The feature vector included features as the computed minimal and maximal force and current measurement value, the standard deviation, the mean, the dominant vibration frequency and others. Per test and training sample a total of 38 features were collected. Depending on the type of data, training or test data, the classifier has been trained or tested. 30 training samples and 20 test samples have been evaluated for each of the eleven terrain types. As classification method, a multiclass implementation of AdaBoost [12] was applied. Since AdaBoost is able to handle weak classifiers, is robust to overfitting and can generate arbitrarily accurate hypotheses [13] it has been considered as adequate for this application. As weak classifiers, simple decision stumps consisting of single-level decision trees, have been used. To deal with multiple classes representing the terrain types the multiclass problem has been reduced to multiple two-class problems.

4. Results

Locomotion in unknown terrain inherently requires the two presented aspects of stable walking and environment (haptic) perception. The first part is achieved through exploitation of the standard gait shown in Figure 6. Thereby, a parallel implementation of the simulated quadruped and the actual hardware provides information about the posture without any exteroceptive sensors leading to a stable walking gait throughout known environment.

Second, the haptic perception capabilities of our system are determined through the evaluation of the classification results. To this end, a confusion matrix was computed: The diagonal elements of the matrix represent correctly classified samples while the other elements indicate wrongly predicted classes. The performance of the classification is evaluated by the parameters success rate (SR) and false alarm rate (FR). Success rate is the ratio between the number of elements of a given class that have been classified correctly and the total number of elements in this class. The false alarm rate, on the other side, describes the number of elements wrongly classified as a certain class compared to the total number of elements that do not belong to this class. Table 2 shows the confusion matrix for the actual terrain type classification, which is additionally visualized in Figure 7. The overall success rate for all the terrain samples was 87%. Solid terrains as asphalt, concrete and ice were classified correctly with a success rate of 98%. The success rate for the classification of soft samples with small particles was 99%. The performance of the classifier was not as good for samples with bigger particles (Slit and gravel with a particle size >4mm). This can be attributed to the fact that the particles arbitrarily jammed the leg motion and therefore generated non-repeatable measurement. Nevertheless, the confusion matrix shows (grey area in Table 2), that almost all of the misclassified gravel samples have been predicted at least as gravel, but with wrong particle size.

Figure 6. Sequence of images of ALOF while walking. For the first steps, a simple gait was implemented in combination with a parallel simulation of posture estimation.
5. CONCLUSIONS

In this paper we presented systems, tools, and concepts to study and improve locomotion in unknown rough and unstructured terrain. We developed a hard- and software system that allows us to focus on the task of perception in legged locomotion. While keeping the robot relatively small and compact, it was built to carry a large payload for additional sensors and designed with a large high range of motion. By including an existing software framework from work done within the learning locomotion challenge, we are able to immediately build on existing solutions for motion planning and execution and can hence focus entirely on research on perception. First walking experiments showed promising performance and proved that the integration worked as expected. Additionally, we intensified our research on foothold selection based on terrain classification methods. As a step toward a real world application, natural terrain types were predicted with a trained classifier. A custom made low cost force sensing device integrated in a robotic leg was used to collect sensor data for the classification process. The classification itself was done by using AdaBoost, a standard machine learning method. Even with very limited amount of training data, the prediction of the terrain type showed good results.

Even though, the test environment we utilized in our study is only a very coarse approximation of a real world scenario, our results pave the road to include additional terrain properties in the definition of the quality of a stance. Going beyond pure geometric definitions of walking stability, we can use the surface properties to generate a holistic assessment of possible footholds and stances. To this end, the different terrain classes that we can recognize must only be rated with respect to the stability they can provide for the robot.

While our experiments describe a first step towards real world terrain classification, the results will only be useful, when they are made available to and can be utilized by a robot. To this end, it might not be necessary
anymore to classify terrain into categories defined by humans, but simply distinguish between terrain that is 'good' or 'bad' for locomotion, i.e. define them in terms in which they are useful for the robot.

Having the tools of stable locomotion with a quadruped and a method for reliable haptic terrain identification in hand, the next step will clearly aim at bringing these elements together. Extended methods could be used to assess terrain properties online while a robot is moving around – either by evaluating the stance feet or following the outlined method by standing on three legs while moving performing experiments with the fourth one. A good estimation of the terrain properties will help to increase the overall stability of legged robots in rough and highly unstructured terrain. Additionally, by relating the experienced haptic information to visual information of the terrain in front of the robot, gait planning could be improved to enhance the overall locomotion performance and create truly autonomous and versatile robotic platforms.

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REFERENCES