

Chapter 1

Related Work

The learning and perception of traversability is a fundamental competence for both organisms and autonomous mobile robots since most of their actions depend on their mobility ?. Usually, visual perception is used in most animals to correctly estimate if an environment can be traversed or not. Similar, a wide array of autonomous robots adopt local sensors to mimic the visual properties of beings to extract meaningful information of the surrounding and plan a safe path through it. This chapter gives an overview of some of the existing traversability estimator approaches.

Most of the methodologies used to estimate traversability rely on supervised learning. Supervised learning is a technique in which first the data is gathered and then a machine learning algorithm is trained to correctly predict the ground truth. These approaches can be clustered into two categories based on the inputs data: geometric and appearance based methods.

1.1 Geometric methods

Geometric methods aim to detect traversability using geometric properties of surfaces such as distances in space and shapes. Those properties are usually slopes, bumps, and ramps. Since nearly the entire world has been surveyed at 1 m accuracy ?, outdoor robot navigation can benefit from the availability of overhead imagery, for this reason, recently, elevation data has been widely used to generate datasets. Chavez-Garcia et al. ?, proposed a framework to learn traversability using elevation data as input in the form of height maps. They trained a convolutional neural network to predict from a dataset, entirely generated through simulation, the traversability probability of a small ground region around the robot.

Elevation data can also be estimated by flying drones. Delmerico et al. ? proposed a collaborative search and rescue system in which a flying robot that explores the map and creates an elevation map to guide the ground robot to the goal. They train on the fly a CNN to segment the terrain in different traversable classes. This map is later used to plan a path for the mobile robot.

1.2 Appearance methods

Appearance methods, to a greater extent related to camera images processing and cognitive analyses, have the objective of recognizing colors and patterns not related to the common appearance of terrains, such as grass, rocks or vegetation. Historically, the collected data is first preprocessed

to extract texture features that are used to fit a classic machine learning classifier such as an SVM [?] or Gaussian models [?]. These techniques rely on texture descriptors, for example, Local Binary Pattern [?], to extract features from the raw data images obtained from local sensors such as cameras. With the rise of deep learning methods in computer vision, deep convolution neural network has been trained directly on the raw RGB images bypassing the need to define characteristic features.

1.3 Mixed methods

One recent example is the work of Giusti et al. [?] where a deep neural network was trained on real-world hiking data collected using head-mounted cameras to teach a flying drone to follow a trail in the forest. Geometric and appearance methods can be used together, one example is the work of Delmerico et al. [?] extended the previous work [?] by proposing the first on-the-spot training method that uses a flying drone to gather the data and train an estimator in less than 60 seconds.

Also, Data can be extracted in simulations, in which an agent interacts in an artificial environment. Usually, no-wheel legged robot able to traverse harder ground, can benefit from data gathering in simulations due to the high availability. For example, Klamt et al. [?] introduced a locomotion planner that is learned in a simulation environment.

1.4 Legged robots

On other major distinction, is between different types of robots: wheel and no-wheel. We will focus on the later since we adopt a legged crocodile-like robot to extend the existing framework proposed by Chavez-Garcia et al. [?].

Legged robots show their full potential in rough and unstructured terrain, where they can use a superior move set compared to wheel robots. Different frameworks have been proposed to compute safe and efficient paths for legged robots. Wermelinger et al. [?] use typical map characteristics such as slopes and roughness gathered using onboard sensors to train a planner. The planner uses a RRT* algorithm to compute the correct path for the robot on the fly. Moreover, the algorithm is able to first find an easy local solution and then update its path to take into account more difficult scenarios as new environment data is collected.

Due to uneven shape rough terrain, legged robots must be able to correctly sense the ground to properly find a correct path to the goal. Wagner et al. [?] developed a method to estimate the contact surface normal for each foot of a legged robot relying solely on measurements from the joint torques and from a force sensor located at the foot. This sensor at the end of a leg optically determines its deformation to compute the force applied to the sensor. They combine the sensor's measurement in an Extended Kalman Filter (EKF). They showed that the resulting method is capable of accurately estimating the foot contact force only using local sensing.

While the previous methods rely on handcrafted map's features extraction methods to estimate the cost of a given patch using a specific function, new frameworks that automatize the features extraction process have been proposed recently. Lorenz et al. [?] use local sensing to train a deep convolutional neural network to predict the terrain's properties. They collect data from robot ground interaction to label each image in front of the robot in order to predict the future interactions with the terrain showing that the network is perfectly able to learn the correct features for different terrains. Furthermore, they also perform weakly supervised semantic segmentation using the same approach to divide the input images into different ground classes, such as glass and sand, showing respectable results.