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Slippage prediction for off-road mobile robots via machine learning regression and proprioceptive sensing

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HIGHLIGHTS

- Slippage prediction associated with individual wheels in off-road mobile robots.
- Machine learning regression algorithms considering proprioceptive sensing.
- Gaussian process regression results in the best accuracy. It also returns the variance associated with each prediction.
- This methodology will be exploited by the layers: path planning and motion control.

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ABSTRACT

This paper presents a new approach for predicting slippage associated with individual wheels in off-road mobile robots. More specifically, machine learning regression algorithms are trained considering proprioceptive sensing. This contribution is validated by using the MIT single-wheel testbed equipped with an MSL spare wheel. The combination of IMU-related and torque-related features outperforms the torque-related features only. Gaussian process regression results in a proper trade-off between accuracy and computation time. Another advantage of this algorithm is that it returns the variance associated with each prediction, which might be used for future route planning and control tasks. The paper also provides a comparison between machine learning regression and classification algorithms.

1. Introduction

Mobile robots operating in off-road conditions must face two key hazards in order to achieve a successful navigation. One of those hazards concerns with the detection and avoidance of geometrical obstacles. This problem is well understood and accounts for a broad body of research [1–4]. Another key challenge related to the mobility of mobile robots in off-road conditions comprises non-geometrical hazards. These hazards depend on the interaction between the robot's wheels and the terrain. For example, a robot traversing loose, sloped sand might experience poor mobility, whereas a robot traversing flat, firm clay might experience excellent mobility [5].

A fundamental phenomenon derived from the wheel–soil interaction is slippage [6–8]. Slippage is a measure of the lack of progress of a wheeled ground vehicle while driving on certain terrains (e.g. sandy slopes, ripples, and low-cohesion soils). Though slippage does not necessarily mean loss of traction. The problem is that excessive slip might cause a loss of tractive effort and rover speed, and eventually robot entrapment [7]. For that reason, it is critical for the success of the robot operation to estimate as accurately as possible the level of slippage of the robot's wheels. The worst situation related to slippage was experienced by the MER Spirit rover which got trapped in a sand dune in 2009. After numerous attempts to free the rover, the mission was declared concluded on May 24, 2011 [9].

Off-road applications also require a robot to depend on simple, on-board sensors to perceive the environment. For example, planetary exploration rovers account for a limited sensor suite mainly composed of one inertial measurement unit (IMU), motor current sensors and encoders on the wheels, and visual cameras. Such

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sensors generally contain significant uncertainty and error in their measurements [5].

This paper provides a methodology where machine learning regression algorithms are used for detecting slippage and its associated uncertainty. This means that slippage is understood as a random variable with a given variance. This variance is associated with the uncertainty derived from the sensors onboard the robot. In addition to that, the proposed machine learning methodology exploits the use of traditional sensors available in off-road robots such as IMU and motor current sensors. Consequently, no operational complexity is added to the rover's commanding and it is independent of lighting conditions (this is an interesting advantage for mobile robots operating in dark or shadowed areas such as mining or greenhouses). The slip derived from this methodology and its associated variance might be ultimately used for modifying the route of the robot and the control actions [10].

This paper is organized as follows. In Section 2, previous work in slip estimation and machine learning regression is reviewed. Section 3 reviews the machine learning regression algorithms considered in this work. Section 4 explains the dataset (data collection) and the set of features considered for training the machine learning algorithms. Section 5 provides experimental results showing a comparison among the regression algorithms presented in this work and other algorithms previously published by the authors and based on machine learning classification [11,12]. Finally, conclusions and future work are drawn in Section 6. The interested reader can see a video of one experiment at: https://youtu.be/kKRSkOrAUdE.

2. Related work

Traditionally slip estimation deals with strategies that result in a continuous value for such variable. It means that slip is given as a real number with a certain precision. For that purpose, those strategies focus on two variables: the wheel angular velocity and the forward velocity of the robot [7]. One of the first methods found in the literature for estimating slip was proposed by Prof. Wong in the 1960s–70s. Slip was directly measured by comparing signals from a wheel placed in front of the robot/vehicle [8]. A simple approach relies on comparison of wheel velocities to a robot body velocity estimate derived from integration of a linear acceleration measurement in the direction of travel (e.g. using accelerometers) [13,14]. Another extended method for estimating rover slip is based on Visual Odometry (VO) [4,6,15]. The main limitation of those approaches is that such single number does not give any information about the uncertainty associated with the estimation and the noise in the measures and sensors.

On the other hand, a new paradigm has recently appeared in the literature and proposed by the authors of this paper [11,12]. It estimates slip as a discrete variable and machine learning algorithms are used for solving this as a classification problem. In particular, a model is trained offline while using a set of proprioceptive measurements. Online computation is then devoted to using such model for predicting the slip in terms of new measurements obtained while the robot is moving. As described in [12], slip belongs to three classes: low slip when slip is between 0 and 30 %, moderate slip when it is within the range 30 and 60%, and high slip when slip is over 60%. Though field tests demonstrate promising results, this approach does not give information about the uncertainty in the estimation.

This paper comes to complete the previous approach. Here, slip is defined as a random variable, the expected value of that variable means the predicted slip and the variance is the uncertainty in such prediction. In particular, this paper solves this problem involving a random variable by using machine learning regression. It bears mentioning that the predicted slip and the uncertainty in such prediction can be certainly useful for both slip compensation [15] and motion planners [16]. The methodology proposed here could complement those approaches by considering routes to a target point where uncertainty in slip is minimized.

The methodology proposed here is based on Gaussian Process Regression (GPR) and slip is understood as a multivariable Gaussian distribution [17,18]. GPR accounts for a broad body of research and has been used by many references, specially in the field of geostatistics as a way to generate terrain models and mobility maps. For example, in [19], a method based on GPR (i.e. Ordinary Kriging) is used for generating a mobility map accounting for measurements errors (i.e. satellite signal) and interpolation error. The path planner is formulated in such a way that routes avoid points of high uncertainty. The work [20] compare different routes using different cost functions and various performance indices. In [21], GPR is used for generating a mobility map based on terrain elevation and wheel slip. Path planning then takes advantage of that map in order to improve vehicle heading and velocity in off-road slopes. For comparison purposes, this paper also takes into account the algorithms: Support Vector Regression (SVR) [22,23], and Kernel Ridge Regression (KRR) [24].

3. Machine learning regression

Machine learning is a branch of computer science based on the study of algorithms that can learn from and make predictions (generalize) on data. There are two main paradigms within machine learning: regression and classification. The first approach deals with taking input variables and forecasting the value of the output (dependent) variable(s). It is based on estimating the relationships among variables (independent and dependent variables) and predicting a numeric value (with an associated variance, in some cases). On the contrary, classification is related to taking input variables and deciding which of N classes they belong to, based on training from exemplars of each class [17]. In this sense, it is based on finding decision boundaries that can be suited to separate out the different classes.

As previously introduced, this paper aims at estimating slippage by means of a regression model derived from training data. More specifically, consider the problem of predicting the slippage, s, of a mobile robot using as input the feature vector $\mathbf{q} \in \mathbb{R}^m$ where $m \in \mathbb{Z}^+$ is the number of features. Each feature is a numerical representation of sensor data that attempts to mimic the sensory cues a human operator would exploit when attempting to detect slippery conditions (e.g. vertical acceleration). The set of features $\mathbf{q}$ is obtained after transforming the raw data coming from proprioceptive sensors onboard the robot (explained in Section 4).

3.1. Gaussian process regression

In this section, the regression model is formulated as a Gaussian Process Regression problem (GPR) [17,18]. The objective is to find a collection of random variables with Gaussian distribution $s(\mathbf{q})$, one for every realization of the input $\mathbf{q}$, such that the joint distribution over any finite subsets of variables is also Gaussian. More specifically, our goal is to identify a functional relationship (regression model) mapping the multi-dimensional input vector, $\mathbf{q}$, on a random variable representing the slippage, s.

Definition 1 (*[18]*)**.** A Gaussian process is a collection of random variables, any finite number of which have a joint Gaussian distribution.

The particularity of Gaussian processes is that they are completely specified by the mean and the covariance. In particular,