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Unsupervised classification of slip events for planetary exploration rovers

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Abstract

This paper introduces an unsupervised method for the classification of discrete rovers' slip events based on proprioceptive signals. In particular, the method is able to automatically discover and track various degrees of slip (i.e. low slip, moderate slip, high slip). The proposed method is based on aggregating the data over time, since high level concepts, such as high and low slip, are concepts that are dependent on longer time perspectives. Different features and subsets of the data have been identified leading to a proper clustering, interpreting those clusters as initial models of the prospective concepts. Bayesian tracking has been used in order to continuously improve the parameters of these models, based on the new data. Two real datasets are used to validate the proposed approach in comparison to other known unsupervised and supervised machine learning methods. The first dataset is collected by a single-wheel testbed available at MIT. The second dataset was collected by means of a planetary exploration rover in real off-road conditions. Experiments prove that the proposed method is more accurate (up to 86% of accuracy vs. 80% for K-means) in discovering various levels of slip while being fully unsupervised (no need for hand-labeled data for training).

Keywords: Unsupervised learning; Clustering; Data-driven modeling; Slip; MSL rover; LATUV rover

1. Introduction

Safely accessing rough and steep terrain is essential to expand access of current and future rovers to planetary surface regions of high scientific value. This goal will reveal clues to the geological, climate, and life history of these bodies and will enable human operations. In particular, challenging terrain such as craters and fault-bounded walls offer natural exposures of the bedrock stratigraphic record, which is key to understanding the geologic record and how environmental and other processes varied over time.

Steep terrain mobility, however, is not limited only to hard surfaces such as cliff faces. Steep terrains can be comprised of loose material at an angle of repose. In this context, one key phenomenon is slip (Angelova et al., 2007; Gonzalez et al., 2014; Iagnemma et al., 2004; Iagnemma and Ward, 2009). Slip means a loss of traction of a wheeled vehicle, which may eventually lead to vehicle entrapment. Notice that the current NASA's Curiosity rover was subject to high slip on sol 672 (June 27, 2014) while crossing sandy ripples (Arvidson et al., 2016). At that time, the algorithm developed by one of the co-authors of this paper, Dr. Iagnemma, halted the progress of Curiosity and waited for instructions from the JPL[1] control center. Even though this algorithm has demonstrated its success, it is only valid for

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traverses over simple, flat courses. Then, it has a limited applicability.

Several researchers have focused on methods to estimate wheel slip by analyzing wheel encoder or torque data (Ojeda et al., 2006), however this technique required terrain-specific parameter tuning, which is undesirable. One of the most extended techniques to estimate rover slip is based on Visual Odometry (VO) (Angelova et al., 2007; Gonzalez et al., 2014; Maimone et al., 2007). Although VO can be an accurate method for slip measurement, it is computationally expensive, which can negatively impact the mean rover drive speed. A second limitation of VO is that on featureless scenarios (e.g. sand dunes), the number of detected and tracked features is low, what can lead to poor accuracy of motion estimate (Johnson et al., 2008). Most recently, researchers have developed methods to estimate slip via stochastic modeling, however, this work was applied to terrestrial systems and thus relies on GPS position data (Rogers-Marcovitz et al., 2012). A potentially simple approach to estimating rover body velocity (and thus slip) is to integrate body acceleration measurements. However, even with high-quality inertial sensing, accurate estimation of body velocity is subject to error and drift (Iagnemma and Ward, 2009). A potentially simple approach for detecting robot slip is based on training machine learning algorithms to recognize distinct levels of slip using proprioceptive signals (Brooks and Iagnemma, 2012, 2005; Gonzalez et al., 2016, 2017; Iagnemma and Ward, 2009; Weiss et al., 2007). These approaches have demonstrated a significant efficiency both in accuracy and in a fast computation. This is the reason why this paper focuses on machine learning algorithms based on proprioceptive signals.

Most of the existing machine learning tasks nowadays focus on information that has been analyzed by human experts who supervise the system and define its goals. However, this leads such systems to possibly break in an unknown environment or when the context changes. In particular, for a planetary exploration rover, correct responses of certain concepts (e.g. high slip instances) cannot be provided, and therefore, supervised machine learning cannot be employed. In this work, we are interested in designing systems that require less supervision and are able to automatically discover important underlying concepts of interest. In this context, unsupervised machine learning can autonomously discover hidden conceptual structures in the data, commonly referred to as clusters. Such unsupervised algorithms identify similarities between the inputs so that inputs that have something in common are categorized together. Therefore, this can reveal concepts such as high/low slip, without any supervision from human experts. Based on such slip levels, one can evaluate the behavior of the rover and take actions accordingly. As an example, a popular unsupervised learning algorithm, self-organizing maps, is exploited in Gonzalez et al. (2017) for slip detection, and does not require high-level slip features in order to create a model of the slip process.

Traditionally, unsupervised learning methods are directly applied on raw data (i.e., original signals). Nonetheless, concepts such as slip level do not clearly manifest in individual sensor readings, but are only discernible over longer periods of time, based on multiple features extracted from the raw data. In this paper, an unsupervised approach for tracking the slip level of planetary exploration rovers based on proprioceptive signals is contributed. The use of proprioceptive sensors represents an interesting alternative to the traditional vision-based approaches, as these approaches demand a high computation and even the visual-odometry-based algorithm may fail in featureless scenarios.

A combination of three important ideas is followed: (i), we *aggregate* the signals over time into a number of statistical features that represent longer periods of interest, sufficient for the concepts of interest to emerge; (ii), we use *unsupervised clustering* over these new features, instead of using the original signals; and (iii) we apply *Bayesian tracking* (Arulampalam et al., 2002), back on the original signals, with the clusters as seeds, to more accurately follow transitions between slip levels.

This paper is organized as follows. In Section 2, we present the data collection and feature selection based on sensor readings. In Section 3, we present our proposed approach. In Section 4, we present the experimental evaluation. Finally, we conclude and present future work in Section 5.

2. Data preparation

Data preparation is a crucial step in any machine learning process (Marsland, 2015). This section presents the data collection and the selection of features that are convenient for our study. A video with the two settings used for collecting the datasets, that is, the MIT single-wheel testbed and the real planetary exploration rover, is available online at: http://web.mit.edu/mobility/videos/embeddingMIT_PI.mp4. Notice that in this work, slip is defined as the difference between the angular velocity measured by a wheel, ω, and the linear velocity of the wheel's center, v, that is, $slip = \frac{\omega r - v}{\omega r}$, where ω is the angular wheel velocity and r is the wheel radius (Wong, 2001).

2.1. Data collection for the MIT single-wheel testbed

The first data set used in this paper was collected using a single-wheel testbed developed by the Robotic Mobility Group at MIT. The system limited the wheel movement primarily to its longitudinal direction. By driving the wheel and carriage at different rates, variable slip ratios can be imposed (Fig. 1a). The bin dimensions are 3.14 [m] length, 1.2 [m] width, and 0.5 [m] depth.

It bears mentioning that the wheel in use for the experimentation was the Mars Science Laboratory (MSL) flight spare wheel. The sensing system of the testbed is composed