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Generation of stochastic mobility maps for large-scale route planning of ground vehicles: A case study

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Abstract

This paper describes a simple and efficient methodology to generate a mobility map accounting for two sources of uncertainty, namely measurement errors (RMSE of a Digital Elevation Model) and interpolation error (kriging method). The proposed methodology means a general-purpose solution since it works with standard and publicly-available Digital Elevation Models (DEMs). The different regions in the map are classified according to the geometry of the surface (i.e. slope) and the soil type. A real USGS DEM demonstrates the suitability of the proposed methodology: (1) interpolation of a $26 \times 40\text{-km}^2$ DEM to a finer resolution (30-m to 20-m); (2) analysis of the number of random realizations to account for the variability of the data; (3) efficient computation time (4-million-point DEM requires less than 30 min to complete the whole process); (4) route planning using the stochastic mobility map (constraints in slope and soil properties). **UNCLASSIFIED: Distribution Statement A. Approved for public release; distribution is unlimited. #27681**

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1. Introduction

A mobility map constitutes a key element in route planning involving ground vehicles (e.g. military operations, planetary exploration missions). Traditionally, those mobility maps are produced considering the average cross-country speed between two points in a given region (speed-made-good maps) (Wong, 2010). This results in a mosaic of terrain units where each unit represents the maximum speed the vehicle could reach. Specifically, the speed map is used for obtaining the route between two points based on the maximum average speed or the minimum time to travel (Wong, 2010).

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The main limitation of those speed maps is that they depend on numerous parameters (and complicated models) dealing with the interaction among the vehicle, the driver, and the operating environment (e.g. sinkage, slope, vegetation, driver's visibility, and tire's characteristics) (Wong, 2010). Another limitation is that terrain units are assumed homogeneous or having uniform features (Haley et al., 1979). The speed map also assumes a steady-state speed for the vehicle. These facts ultimately mean the speed map is difficult to calculate (many parameters and models) and its results may be unrealistic or too conservative (Wong, 2010). Additionally, to date, the process followed to obtain speed maps do not include the effect of measurement errors and uncertainty in the parameters involved in the process.

This paper describes a simpler framework than the traditional speed map. The proposed methodology means a general-purpose solution since it works with standard and publicly-available DEMs (USGS, 1998). Additionally, measurement errors due to sensor noise and the gridding process performed to produce the DEM (i.e. RMSE of USGS DEMs), and interpolation errors due to a downsampling process (kriging method) are both considered. The result of the proposed framework is a stochastic mobility map where regions are classified according to the geometry of the surface (i.e. slope) and the soil type (Unified Soil Classification System, USCS) (Garcia-Gaines and Frankenstein, 2015). More specifically, the stochastic mobility map represents with a specific level of certainty if a region is traversable or not, such threshold is specified by the decision maker (e.g. 70% of the N random realizations a point is classified as GO). Another advantage of the proposed approach is that it leads to an efficient computation time, which is clearly advisable in this context where large data sets are employed. It bears mentioning the produced stochastic mobility map can be used for calculating the optimal route between target locations where the NOGO regions should be avoided. This point is also validated in this paper.

This paper is organized as follows. In Section 2, the state of the art is reviewed. Section 3 describes the proposed methodology to calculate the stochastic mobility map. The implications of the stochastic conditional simulation required for accounting the variability in the data is addressed in Section 4. A study case demonstrating the suitability of the proposed methodology is addressed in Section 5. Section 6 discusses the role of soil moisture in the mobility prediction problem. In Section 7, conclusions are drawn and future work is suggested.

2. Related work

Using speed maps for predicting the mobility of cross-country vehicles emerged in the military field by the mid-1960s. The work in Rula and Nuttall (1971) summarizes a compendium of existing ground mobility models illustrating cross-country vehicle performance. Here, the authors state that the primary terrain attributes of interest to cross-country vehicle operation are those describing the geometry of the surface (i.e. slope), and the strength of the material in it (i.e. soil type). Based on the recommendations and guidelines suggested by those authors, the first edition of the known NATO Reference Mobility Model (NRMM) appeared in 1979 (Haley et al., 1979). The NRMM is a computer-based simulation tool that can predict a vehicle's steady-state operating capability (effective maximum speed) over specified terrain. In this sense, the output of the NRMM is a speed-made-good map where terrain units are classified using a collection of equations and algorithms. Those equations take into account many attributes describing surface composition, surface geometry, vegetation, vehicle, and driver. The key role of obstacles and surface roughness in the production process of those speed maps is discussed in Richmond (2012). This research also reveals the need for having high resolution maps for detecting and representing obstacles.

To date, the only effort devoted to converting NRMM from a deterministic framework to a stochastic one appears in Lessem et al. (1996). More specifically, the input parameters to the NRMM are randomly generated according to a given range, after some Monte Carlo simulations an output is obtained while considering the nominal, maximum, and minimum speeds that a vehicle could achieve for a particular scenario. However, this approach fails in the core component of a stochastic procedure, that is, the origin of uncertainty. In Lessem's work, uncertainty is simulated via a fixed range for every input parameter. Those ranges are assigned after expert opinions, but not a formal mathematical background is on this decision. Even those ranges do not come from experimental evidence.

Other known simulation tools for evaluating the performance of cross-country military vehicles are: NTVPM and NWVPM (Wong, 2010). Both tools rely on physics-based computer-aided methods that are used for predicting the cross-country performance of single-unit or two-unit articulated vehicles with either tracks or wheels. Despite these methods have demonstrated its suitability both in large heavy vehicles (Wong, 2010), and a small lightweight track system (Wong et al., 2015); they have not been used for large-scale route planning.

A substantial body of work has been performed on mobility prediction in the context of mobile robots or unmanned vehicles operating in off-road conditions both using geometrical maps (Goldberg et al., 2002; Thrun et al., 2006) or speed maps (Loh, 2012). However, the majority of that research copes with 3D path planning in the vicinity of the robot. Thus, those approaches are generally not appropriate for planning long routes over large environments (e.g. Curiosity rover over a large Martian region or a military vehicle over a battle field).

Regarding the issue of route (or path) planning over large-scale routes, an important research effort has been made combining remote data with ground data. The focus of that work has been mainly on the fields of obstacle avoidance (Stentz et al., 2003), robot location (Vandapel et al., 2006), and slip prediction (Angelova et al., 2007). The work in Kang et al. (2011) addresses the path planning problem in the context of unmanned military missions. This particular context explains some of the factors considered: slope of the terrain, degree of bumpiness in various land-uses, and exposure to enemies.

Finally, it is important to highlight some papers where uncertainty has been taken into account for predicting vehicle performance. For instance, in Peynot et al. (2014), the authors define mobility prediction as the problem of estimating the likely behavior of a planetary exploration rover in response to given control actions on a given terrain. In this sense, uncertainty is in the control rather than in the DEM/terrain map. In Ishigami et al. (2009), a statistical method for mobility prediction considering uncertainty in terrain physical properties (cohesion and