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An efficient method for increasing the accuracy of mobility maps for ground vehicles

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Abstract

This paper presents an efficient method for increasing the accuracy of one key step regarding the process of determining a mobility map. That is, the interpolation of the original Digital Elevation Model (DEM) to a finer resolution before running multi-body-dynamics simulations. Specifically, this paper explores the use of fractal dimension and elevation range metrics for increasing the accuracy and reducing the computation time associated with the spatial interpolation ordinary kriging method. The first goal is to ensure the stationary variogram requirement. The second goal is to reduce kriging error or variance in the new predicted values. A novel segmentation-based approach has been proposed to divide the regions of interest into segments where stationarity is ensured. Empirical investigation based on real DEMs indicates the generality of the segmentation approach when natural and man-made terrains are considered. The proposed method leads to a more efficient computation burden and to more accurate results than the traditional approach.

Keywords: Mobility prediction; NATO Reference Mobility Model (NRMM); Variogram; K-means; Man-made environment

1. Introduction

A mobility map constitutes a fundamental element in route planning involving ground vehicles (e.g. military operations, planetary exploration missions). Those mobility maps are produced for predicting the motion of a vehicle over a given region. This mobility is analyzed while considering certain parameters illustrating 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). It is clear that in order to obtain reliable and successful predictions the resolution of such mobility map should be as high as possible. The contribution of this paper deals with one key issue of a mobility map, that is, the elevation map related to the terrain where the vehicle is going to operate and how to interpolate such elevation map to a finer resolution (Gonzalez et al., 2016; Hadsell et al., 2010; Kweon and Kanade, 1992; Papadakis, 2013).

The field dealing with the problem of analyzing remote sensing data is called geostatistics (Bechler et al., 2013; Cressie and Kang, 2010; Tardic et al., 2014; Tsui et al., 2013). In this field, the ordinary kriging method has been widely used for creating a continuous surface from a sparse dataset or for increasing the resolution of a map. This method requires a model of the environment to obtain the new interpolated points and their associated variance or uncertainty; this model is called variogram (Chiles and Delfiner, 2012; Isaaks and Srivastava, 1989; Webster and Oliver, 2007). In this sense, kriging variance (kriging error or kriging uncertainty) is a function of the form of the variogram model and, thus, improving the accuracy of the var-

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iogram leads to increasing the accuracy of kriging (i.e. by resulting in a smaller variance/uncertainty for each new interpolated point).

On the other hand, ordinary kriging is based on the assumption of a stationary variogram, and this requires that the mean and variance of such variogram is finite and constant in the area under investigation (Fisher, 1998). However, in practice this assumption is not always ensured(Atkinson and Lloyd, 2007; Chen and Li, 2012; Lloyd and Atkinson, 1999). This fact is especially noticeable when a global variogram intends to capture the nature of a heterogeneous environment (e.g an environment with man-made and natural-terrain regions). To solve the issue of non-stationary variogram, different approaches have been proposed in the literature. Such approaches can be grouped into the following three categories (Zhang et al., 2014): (i) locally-adaptive kriging involves predicting and modeling the local experimental variogram and using the coefficients of the locally fitted model in (the local) kriging; (ii) surface deformation aims to distort a surface such that a stationary variogram results from data in transformed space; and (iii) segmentation involves dividing the region of interest into smaller segments within the variogram can be considered stationary, thus allowing for local application of geostatistical optimal sampling design in their study.

The most common approach is based on segmentation (Atkinson and Lloyd, 2007; Chen and Li, 2012; Darbeheshti and Featherstone, 2010; Lloyd and Atkinson, 1999). However, some of those references divide the region of interest by using a predefined template or rule, for instance, dividing the environment into four segments each time non-stationarity is found during the segmentation (Chen and Li, 2012). The main drawback of this approach is that it does not take advantage of the properties of the local variograms in order to increase the accuracy of the segmentation step. The procedure proposed in this paper is inspired by Atkinson and Lloyd (2007) and Lloyd and Atkinson (1999), where a clustering segmentation algorithm is employed. The metrics on which the segmentation was based is the fractal dimension (Klinkenberg and Goodchild, 1992). The main limitation of Lloyd's method is that fractal dimension cannot be applied when the region of interest does not fulfill Brownian properties, as explained in Kroese and Botev (2014). In this sense, the novelty of the approach proposed here comes from combining fractal dimension with elevation range in the segmentation step. This method will lead to a more general solution since it can be applied to any kind of terrain profile. Notice that the elevation range constitutes a well-known metrics in the field of geomorphology, which has been mainly used for identifying and classifying terrains (Evans, 2012; McClean and Evans, 2000; Saadat et al., 2008).

Notice that this work is framed in the context of the next-generation NATO Reference Mobility Model (NRMM) military software (the current software is described in Haley et al. (1979)). One requirement of the next-generation NRMM is that such software should be executed on computers available onboard military vehicles or in military camps in battle fields. In this regard, the proposed approach means an efficient solution in terms of computation burden, and demonstrates its suitability on a standard-performance computer (Intel Core i7, 3 GHz, 16 MB RAM).

This paper is organized as follows. Section 2 briefly introduces the mathematical background related to ordinary kriging. After that, the proposed segmentation-based interpolation method is described in Section 3. Illustrative examples demonstrating the suitability of the proposed method are discussed in Section 4. Conclusions and future work are explained in Section 5.

2. Mathematical background. Kriging

Kriging constitutes a well-known point estimation method in the field of geostatistics (Chiles and Delfiner, 2012; Isaaks and Srivastava, 1989; Webster and Oliver, 2007). Kriging belongs to Gaussian process regression where the interpolated values are calculated by taking into account a model derived from the own spatial correlation of the data, namely the variogram. In geostatistics, this method not only yields a higher resolution surface, but also the estimates of error in those new interpolated points (error map) (Chiles and Delfiner, 2012; Webster and Oliver, 2007). This estimate of error can be used for predicting the mobility of a ground vehicle while considering uncertainty in elevation (Gonzalez et al., 2016).

Following the OK formulation, at every point where the elevation is unknown, it is interpolated via a weighted linear combination of the available samples (Isaaks and Srivastava, 1989)

$$\widehat{Z}(s_0) = \sum_{i=1}^{N} w_i Z(s_i), \tag{1}$$

where $\widehat{Z}(s_0)$ is the estimated elevation of the sample located at s_0, N is the number of samples, and w_i are the weights for the linear combination of known samples $Z(s_i)$.

Ordinary kriging minimizes the mean squared error of prediction

$$\min \ \sigma_e^2 = \mathbb{E}\left[Z(s_0) - \sum_{i=1}^{N} w_i Z(s_i)\right]^2 \ s.t. \sum_{i=1}^{N} w_i = 1. \tag{2}$$

As shown in (Isaaks and Srivastava, 1989), the mean squared error can be written as

$$\sigma_e^2 = 2\sum_{i=1}^{N} w_i \gamma(s_0 - s_i) - \sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \gamma(s_i - s_j). \tag{3}$$

The key issue of kriging is that in order to obtain the coefficients appearing in (1) a model of the spatial correlation between the available samples is employed. This terrain model is the variogram (Chiles and Delfiner, 2012;