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Modeling the precision of structure-from-motion multi-view stereo digital elevation models from repeated close-range aerial surveys

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ABSTRACT

The accuracy of digital elevation models (DEMs) derived from structure-from-motion (SFM) multi-view stereo (MVS) 3D reconstruction is commonly computed for a single realization of model elevations. This approach may be adequate to estimate an overall measure of systematic error; however, it cannot provide a good estimation of measurement precision. Knowing measurement precision is crucial for measuring elevation surface changes observed by DEM comparisons. In this paper, we illustrate an approach to characterize spatial variation in the precision for SFM-MVS derived DEMs. We use a snow-covered surface of an active rock glacier located in the southern French Alps as the case study. A spatially varying precision estimate is calculated from repeated close-range aerial surveys for a single acquisition period by calculating the standard deviation per grid cell between the DEMs created for each flight repetition. Regression analysis using a generalized additive model (GAM) is performed to model the estimated precision and provide insights regarding how sensor, survey design and field site conditions may spatially influence the measurement precision. Additionally, we define how DEM error can be described differently depending on the available validation data. In our study image height above ground level and distance to ground control points had the greatest explanatory power for spatial variation in DEM precision. Image overlap, mean reprojection error and saturation were also useful for explaining spatially varying measurement precision of the DEMs. Field site characteristics, such as slope angle and shading, had the least importance in our model of precision. From a practical point of view, regression-modeled relationships between precision and image and site characteristics can be utilized to design future surveys with similar sensing platforms and site conditions for improved DEM precision.

1. Introduction

One of the most recent developments in digital elevation model (DEM) generation methods is the use of structure-from-motion (SFM) and multi-view stereo (MVS) 3D reconstruction techniques (James and Robson, 2012; Westoby et al., 2012; Micheletti et al., 2015b; Smith et al., 2015; Carrivick et al., 2016). In general, these techniques can create a 3D reconstruction of a surface from a collection of images for a given feature taken from a variety of viewing angles (Snavely et al., 2006). It has become vastly popular for geosciences applications (see Carrivick et al., 2016 for an extensive list). As with the use of any DEM, it is crucial to understand the quality of the SFM-MVS derived DEMs to ensure the suitability for a particular application.

The quality of DEMs can be described by analyzing its errors (Fisher, 1998). In general, all DEMs inherently contain some error (Fisher and Tate, 2006), and systematic and random error structures can vary between different sensors and survey designs (Wilson, 2010). These errors will propagate to DEM derivatives, such as slope, aspect and the hydrologic or geomorphic models that utilize these derivative products (Holmes et al., 2000; Walker and Willgoose, 1999). As a result, DEM error can contribute to the uncertainties related to monitoring Earth surface changes (Brasington et al., 2000; Burns et al., 2010; Wyrick and Pasternack, 2016). A model of DEM error can be developed to characterize DEM uncertainty for a particular survey technique and site (Holmes et al., 2000; Wheaton et al., 2010; Tinkham et al., 2014; Bangen et al., 2016). Such a model can be used to not only determine possible sources of errors, but also to improve methods of DEM production (Fisher, 1998; Carlisle, 2005; James and Robson, 2014; James et al., 2017b).

The most common approach to modeling the spatial variation in DEM errors has typically been to stochastically simulate DEM error distributions (Fisher, 1998; Fisher and Tate, 2006; Kyriakidis et al.,

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1999; Holmes et al., 2000; Wechsler and Kroll, 2006). Recently, such an approach has been applied to assess error in SFM-MVS elevation models using Monte Carlo simulation; in particular, the authors evaluated how survey design may influence the distribution of precision in a DEM (James et al., 2017a,b). Since there are numerous factors that can lead to errors in the SFM-MVS DEM (Smith and Vericat, 2015), it is possible that the simulation approach could potentially overlook factors, such as field conditions (Favalli et al., 2012), that may affect the distribution of error in DEMs derived from SFM-MVS 3D reconstruction.

The purpose of this study is to assess DEM error by estimating measurement precision of SFM-MVS derived DEM values to characterize how precision may spatially vary and to explain this variability. Repeat aerial surveys from an unmanned aerial vehicle (UAV) can be used to create multiple DEMs for estimating precision. This approach computes the precision for individual grid cells of the DEM image of surface elevations. That is, we estimate the precision corresponding to each grid cell. In this way, we are treating each grid cell as a separate measurement, and we are using a model of error that allows for the values of precision to vary spatially. Additionally, a generalized additive model (GAM), a nonlinear statistical regression technique, is used for characterizing the spatial variation in precision by modeling the respective influences of sensor, survey and field site conditions.

2. Describing DEM measurement error

Typically, analysis of the spatial pattern of errors in DEMs focuses on the difference between the measured values and some ‘true’ value that is perceived as more accurate (Smith and Vericat, 2015; Kyriakidis et al., 1999); i.e. where the reference data used for validation is considered as the ‘truth’. In this paper, we focus on measurement bias, the mean difference between measured values and some ‘true’ value, to describe the pattern of error. Bias can be used to describe the presence of systematic error, which is the tendency of measurements to, on average, under- or overestimate the ‘true’ values. Additionally, we define precision of a measurement as the variability in values between multiple observations. It can be used to describe random error, and can be assessed in terms of reproducibility or repeatability.

Most SFM-MVS studies in the geosciences have focused on reproducibility (Clapuyt et al., 2016; Smith and Vericat, 2015). Reproducibility can be defined as how measurements vary using different sensors under different conditions, including different periods (Bartlett and Frost, 2008). These studies are popular for good reasons: they seek to optimize experimental parameters to produce the best 3D reconstruction results for a variety of sensor and field conditions (e.g., Clapuyt et al., 2016); they also demonstrate the capability of the SFM-MVS approach to produce high resolution and high quality DEMs suitable for studies of Earth surface processes and landforms. There are many factors that affect elevation modeling results, some examples of reproducibility include comparisons of: SFM MVS pipelines from different software (Smith et al., 2015; Micheletti et al., 2015a; Ouédraogo et al., 2014; Stumpf et al., 2015; Dandois et al., 2015); sensors/cameras (Micheletti et al., 2015a; Dandois et al., 2015), camera settings and calibration (Clapuyt et al., 2016; James et al., 2017b; Harwin et al., 2015), flight plans (Smith and Vericat, 2015; James and Robson, 2014; Dandois et al., 2015), the distribution of ground control (Tonkin and Midgley, 2016; James et al., 2017a; Clapuyt et al., 2016), different field sites (Dandois et al., 2015; Nolan et al., 2015; Harder et al., 2016; Bühler et al., 2016); variable field site conditions (Dandois et al., 2015; Harder et al., 2016; Harwin and Lucieer, 2012; Westoby et al., 2012) and georeferencing approaches (Carbonneau and Dietrich, 2017).

Repeatability can be defined as how a measure varies for a particular sensor and involves conducting repeat measurements of the same object with the same sensor under similar conditions within a short period (Bartlett and Frost, 2008). That is, repeatability investigates what would be the expected variation in elevation measurement for a given UAV survey for a given camera, survey design and field site conditions. Using repeat observations for determining measurement precision is a well-known approach for assessing measurement uncertainty, but has yet to be commonly applied for DEMs, in particular for SFM-MVS DEMs. This study focuses on repeatability.

Throughout this section, we define several models that can be used to describe the distribution of DEM error. Each error model is based on a scenario that depends on the data collected or available for error analysis. These scenarios are, (i.) single DEM from an aerial survey with surveyed check points or a reference DEM; (ii.) multiple DEMs from repeat aerial surveys with surveyed check points; or (iii.) multiple DEMs from repeat aerial surveys with a reference DEM. The error models mathematically characterize and define the error components for each of these different situations and subsequently define estimators for the bias and precision. In doing so, we present characterizations of bias and precision that are allowed to vary spatially depending on the surveying scenario and thus data availability. The error models presented here are not meant to be a comprehensive list; we acknowledge that there are other approaches to error analysis of SFM-MVS DEMs such as those based on simulations (James et al., 2017b). Instead, we present the most commonly applied error model (i.e., i.) and demonstrate how we can afford more complex descriptions of error by providing additional repeat survey data (i.e., ii. and iii.).

The elevation value $y(x)$ of a surface (e.g. a SFM-MVS derived DEM) within domain D can be described as,

$$y(x) = z(x) + e(x) \tag{1}$$

where $z(x)$ is the ‘true’ elevation value and $e(x)$ is the measurement error at location x. Typically, $e(x)$ is determined by comparing $y(x)$ to a reference data set to represent $z(x)$ at a higher accuracy, where the number n of reference elevations $(z(x))_{x \in D}$, $i = 1, \ldots, n$ can either be a set of check points, for example from a Global Navigation Satellite System (GNSS) survey, or elevations from another DEM (Kyriakidis et al., 1999).

2.1. Single DEM with check points or a reference DEM

The most common approach for describing measurement error in DEMs, both classically and within SFM-MVS studies, is the use of global statistical measures, such as root mean square error (RSME), mean error and the standard deviation (SD) of error at check point locations (Fisher and Tate, 2006; Wilson, 2010; Smith et al., 2015). These statistics describe the overall measurement error of a DEM and, given a spatially distributed set of reference data, can provide a visualization of spatial error patterns. Usually, these statistics are calculated for the scenario where a close-range aerial survey is used to produce a single SFM-MVS DEM to measure the elevations of a surface, and some sort of reference data has been collected.

We describe the measurement error $e(x)$ in this situation by decomposing it into a constant bias or systematic error, μ, and a random error, $\varepsilon(x)$:

$$e(x) = \mu + \varepsilon(x). \tag{2}$$

The random error in this conceptual model has a mean of 0 and standard deviation σ, and it is often observed or assumed to be normally distributed (James et al., 2017b; Kyriakidis et al., 1999; Fisher and Tate, 2006).

The standard deviation, or precision, is estimated as the standard deviation σ of measurement error, or the square root of the measurement error variance σ^2,

$$\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}(e(x_i) - \widehat{\mu})^2 \tag{3}$$

where $e(x_i)$ is the difference between the elevation surface and reference data, $y(x_i) - z(x_i)$, at locations for $x_i \in D$, $i = 1, \ldots, n$. That is, the measurement precision is based on an estimate of the standard