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Bathymetry fusion using multiple-point geostatistics: Novelty and challenges in representing non-stationary bedforms

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ABSTRACT

In large rivers, complex sediment dynamics cause rapid changes in the position and shape of bed deposits. Regular monitoring of changes in river bed geometry is essential for assessing the nature of morphological change and associated bed load during low, high, and medium flow conditions. We demonstrate the application of Direct Sampling (DS) for patching partial river morphological surveys to generate complete maps of the river morphology, by incorporating prior knowledge from bathymetry data collected in different seasons at collocated or adjacent reaches. This novel approach is based on multiple-point statistics (MPS), which uses a training image (TI) to provide prior statistical and architectural constraining data. In this study high and low resolution bathymetry data from a reach of the Mississippi river have been used. High-resolution measurements were conducted using Multi-beam-echo-sounder (MBES), which provides very detailed bed geometry at high spatial resolution. These measurements cannot be acquired at intervals frequent enough to characterize the rapid sedimentological processes. Low resolution bathymetry data can be obtained at frequent intervals but at sparse locations, by installing depth measuring sensors on boats passing the study reach several times a week. The DS method is used to simulate the high resolution bathymetry at the frequency of the low-resolution data. In the simulations, the method uses the bed geometry information contained in the MBES high-resolution surveys, the local information contained in the boat-borne low-resolution measurements, and provides an updated bathymetry map with quantified uncertainty.

1. Introduction

Accurate estimation of bathymetry is necessary for evaluating changes in river-channel morphology (Fonstad and Marcus, 2010), determining reservoir volume (Furnans and Austin, 2008), water quality modeling (Mantas et al., 2011), providing boundary conditions for numerical modeling of flow dynamics and sediment transport (Liu et al., 2012), and for measuring the movement of sediment in the waterway (Jiang et al., 2011). The impact of sediment dynamics on spatio-temporal patterns of erosion and deposition is evaluated by observing the differences in digital elevation models, which are created from repeat bathymetric surveys (Fuller and Basher, 2013).

In shallow rivers and coastal areas, there is growing interest in using remote sensing to accurately estimate the bathymetry (Legleiter and Roberts, 2009). A variety of measurement tools for remote bathymetry surveying are available, including satellite imagery (Stumpf et al., 2003), LiDAR technology (Bailly et al., 2010) or a combination of these methods (Coleman et al., 2011; Legleiter, 2013). However, these methods fail to retrieve the bathymetry of deep and turbid rivers. In such cases, Multi-beam-echo-sounder (MBES) sonar systems have been employed in recent decades to measure the bed morphology in oceans, deep lakes and rivers (Simmons et al., 2007). MBES has the advantage of covering large areas with each individual LASER pulse, or ping of sound, and thus scans distinguishable morphological patterns at the river bottom at high-accuracy and high-resolution spatial scales (Costa et al., 2009; Cutter et al., 2003; Masetti and Calder, 2012). In large rivers, the bed shape can change rapidly as a consequence of morphodynamic processes. Accurately and efficiently keeping track of the changes in bathymetry requires frequent detailed surveys. Although MBES

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provides high-resolution data, the high cost prevents its regular use (Quinn and Boland, 2010). The alternate option of Single-beam-echo-sounders (SBES) bathymetry surveying is inexpensive and can be used to rapidly obtain low-resolution data. However, SBES provides inadequate gap-free data (Jena et al., 2012). An economically feasible option is to conduct detailed surveys at specific intervals, for example after extreme events, and then update the maps using low resolution but cost-effective data.

Various methods have been proposed to integrate bathymetry data from multiple sources including bathymetry fusion (Elmore and Steed, 2008) or bathymetry merging (Gesch and Wilson, 2002). Merging or fusion of bathymetry data has been used to improve the resolution of a historical topography map with satellite imagery (Alcântara et al., 2010), to combine observation of two satellites (Sindhu et al., 2007) and to enhance satellite imagery with bathymetry data obtained from LiDAR (Calder, 2006; Wozencraft and Millar, 2005). However, to the best of our knowledge, there is a scarcity of approaches for updating high-resolution infrequent bathymetry surveys with more frequent but lower resolution data. This is a challenging problem because it involves integrating data types of a very different nature. The infrequent high-resolution surveys provide accurate bed feature information such as the shape and size of the sand bars, the spatial frequency of their occurrence or the spatial continuity of deeper areas. However, the local information in these surveys is quite weak. Given the rapid changes in the river bathymetry, any survey – no matter how accurate – is likely to be outdated in a couple of months (or days during high flow periods). The boat-mounted acoustic measurements (SBDM) are frequent enough to be locally accurate; however they only cover a limited area. Therefore, it would be desirable to have the ability to extract the bed feature properties of the MBES data, and adapt them such that locally they correspond to the SBDM measured values. Ideally, away from these measurements the bathymetry should still present a similar spatial morphology and bed features as observed in the MBES survey, but with an associated uncertainty due to the lack of local information.

Geostatistics is a natural tool for analyzing spatially correlated variables. Ordinary kriging is commonly used in interpolating river channel bathymetry to obtain bed topography (Carter and Shankar, 1997; Chappell et al., 2003; Legleiter and Kyriakidis, 2008; Merwade, 2009; Merwade et al., 2006). Cokriging algorithms have been applied in the mapping of bedforms by considering bathymetry, slope, and sediment input (Jerosch, 2012). Using such approaches, the integration of newly measured data to the already developed base map would require the updating of variogram parameters (Barnes and Watson, 1992) and kriging to obtain an updated surface (Jha et al., 2011). However a fundamental issue is that kriging is based on linear geostatistics, which assumes that the mean and variance of the increments are spatially stationary (Goovaerts, 1997), and provides smooth interpolated values at unsampled locations by giving more weight to local neighborhood data than the global statistical properties (Journel and Huijbregts, 1978). More generally, linear geostatistics are not designed to represent low entropy patterns and salient features such as those formed by river flow mechanisms (Journel and Zhang, 2006). A detailed representation of bathymetry patterns is however critical because these patterns exert a strong influence on sediment transport (Shelley et al., 2013), and control the flow mechanisms in and out of the river bed (Gooseff et al., 2006). The smoothed representation typical of kriging approaches is therefore not appropriate for certain types of applications.

The issue of smoothing with kriging and the need to represent specific patterns motivated the development of multiple-point geostatistics (MPS) (Guardiano and Srivastava, 1993). MPS is a non-parametric approach, and as such it is free from linearity or multi-Gaussianity assumptions (Gómez-Hernández and Wen, 1998). The main feature of MPS is that it uses training images to describe complex patterns of spatial continuity. In this paper we solve the integration of bathymetry data collected at different resolutions and at different time periods using an approach based on MPS.

Most MPS techniques derive arrangements of values from a training image and store them in a database (Strebelle, 2002). The database is then used to retrieve the conditional probabilities for the simulation. Early MPS methods such as SNESIM (Strebelle, 2002) were aimed at simulating categorical variables, for example geological facies or land use classes (Boucher et al., 2008; Feyen and Caers, 2006). However, recent MPS algorithms such as SIMPAT (Arpat and Caers, 2007), FILTERSIM (Zhang, 2006), and Direct Sampling (Mariethoz et al., 2010) allow for the use of continuous variables like bathymetry. In this paper, we use Direct Sampling (DS), which compared to other continuous-variable based MPS methods, has a number of advantages relevant for applications to bathymetry:

1) It does not require a database of patterns, and is therefore memory efficient and can handle very large data sets;
2) It is very effective for data conditioning because it does not use systems such as data templates or multiple-grids, which require approximations on the conditioning data locations; and
3) It allows using multivariate training images, and this possibility can be used to take into account complex non-stationarity, which is a common feature for bathymetry data.

Recently, DS has been successfully applied in the stochastic downscaling of climate models (Jha et al., 2013), the completion of partially-informed remote sensing images (Mariethoz et al., 2012) and the incorporation of prior geological concepts in subsurface models (Mariethoz and Kelly, 2011). In this study DS is used to merge the infrequent detailed information contained in MBES bathymetric surveys and data collected at a higher frequency but with partial coverage by boat-borne surveys. Patterns contained in MBES data recorded during the highest and lowest river-flows are used as training images. The patterns in those training images are conditioned to the more recently acquired SBDM data, which results in an updated map of bathymetry that is accurate at the sparse locations measured at high frequency, and which honors the patterns observed in the detailed but infrequent MBES surveys. To the best of our knowledge, this is the first time two equiprobable training images have been used in a DS simulation to provide the complete range of values for a single intermediate state.

2. Methodology

The methodology adopted to update the river bathymetry is based on the Direct Sampling (DS) geostatistical simulation approach. It generates realizations of a variable Z that present the same spatial continuity as a given training image, and given conditioning data. The inputs are therefore a training image, a simulation grid, and a set of conditioning data. The nodes of the simulation grid are visited sequentially in a random order. For each simulation grid node, the pattern formed by the neighboring values is defined, and the training image is sampled to find a representative location having a similar neighborhood. The value at this representative location is then pasted in the simulation grid.