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From picture to porosity of river bed material using Structure-from-Motion with Multi-View-Stereo

Lydia Seitz [a,*], Christian Haas [b], Markus Noack [a], Silke Wieprecht [a]

[a] Institute for Modelling Hydraulic and Environmental Systems, University of Stuttgart, Stuttgart, Germany
[b] I AM HYDRO GmbH, St. Georgen, Germany

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ABSTRACT

Common methods for in-situ determination of porosity of river bed material are time- and effort-consuming. Although mathematical predictors can be used for estimation, they do not adequately represent porosities. The objective of this study was to assess a new approach for the determination of porosity of frozen sediment samples. The method is based on volume determination by applying Structure-from-Motion with Multi View Stereo (SfM-MVS) to estimate a 3D volumetric model based on overlapping imagery. The method was applied on artificial sediment mixtures as well as field samples. In addition, the commonly used water replacement method was applied to determine porosities in comparison with the SfM-MVS method. We examined a range of porosities from 0.16 to 0.46 that are representative of the wide range of porosities found in rivers. SfM-MVS performed well in determining volumes of the sediment samples. A very good correlation ($r = 0.998$, $p < 0.0001$) was observed between the SfM-MVS and the water replacement method. Results further show that the water replacement method underestimated total sample volumes. A comparison with several mathematical predictors showed that for non-uniform samples the calculated porosity based on the standard deviation performed better than porosities based on the median grain size. None of the predictors were effective at estimating the porosity of the field samples.

1. Introduction

The porosity of sediment samples of river bed material is defined as the relation of pore volume to total volume and is a geomorphologic parameter to describe sediment characteristics. It is influenced by the size, distribution and shape of individual sediment grains (Fraser, 1935; Graton and Fraser, 1935). Among other parameters, it can be used as a descriptive variable for reproduction habitats of gravel-spawning fish as well as for habitats of juvenile and benthic fish or macroinvertebrates (Bunte and Abt, 2001; Noack, 2012). Porosity can be reduced from intrusion and deposition of fine sediments in the pore space. This process, known as colmation (e.g., Schälchli, 1992; Brunke, 1999), clogs the pores, which limits the physical habitat space for juvenile fish and macroinvertebrates (Richards and Bacon, 1994; Buendia et al., 2013; Descloux et al., 2013) and reduces the transport of dissolved oxygen into the hyporheic interstitial (Greig et al., 2007; Heywood and Walling, 2007; Sear et al., 2008). This can, in turn, significantly increase egg mortality of salmonid embryos (Sear et al., 2016). Clogged pore space also reduces the survival of alevins during emergence (Gustafson-Greenwood and Moring, 1991; Kemp et al., 2011) by preventing their upward migration to the stream bed (Kondolf, 2000). A negative correlation between porosity and macroinvertebrate density as well as taxon richness within the bed sediment is also reported in literature (Maridet et al., 1992; Gayraud and Philippe, 2003; Bo et al., 2007). Noack et al. (2017) modelled the availability of interstitial habitat suitability of brown trout and found a decrease of interstitial habitat suitability with decreasing hydraulic conductivity caused by the infiltration of fine sediments.

During recent decades, porosity has been the focus of various studies (Carling and Reader, 1982; Yu and Standish, 1991; Wu and Wang, 2006; Wooster et al., 2008; Frings et al., 2011; Zou et al., 2011; Capece et al., 2014; Liang et al., 2015). The porosity n is calculated by the volumetric proportion of pore space and sediment volume:

$$n = \frac{V_P}{V_{tot}} = 1 - \frac{V_{tot} - V_{Se}}{V_{tot}} \tag{1}$$

with either a known pore volume V_P and total sample volume V_{tot}, or a known V_{tot} and the particle volume V_{Se}. In principal, three options are available to assess the porosity of river bed sediments: (i) in-situ field measurements, (ii) laboratory measurements or (iii) estimation based on mathematical predictors. A common but time-consuming method to identify porosity on site or in the laboratory is the water replacement method (WRM, e.g., Frings et al., 2011; Bunte and Abt, 2001). One

* Corresponding author at: Institute for Modelling Hydraulic and Environmental Systems, University of Stuttgart, Pfaffenwaldring 61, 70569 Stuttgart, Germany.
E-mail address: lydia.seitz@iws.uni-stuttgart.de (L. Seitz).

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possible way to apply WRM can be found in the guidelines from the American Society of Testing and Materials (2004) in which the sediment is first removed from the location of interest, then the excavation is covered with a liner and filled with water in order to measure V_{tot}.

To analyze the porosity of sediment samples in laboratories, several methods are available. Exemplary methods include the gas pycnometer, following Boyle's Law of volume-pressure relationships, or the water desorption method (Klute, 1986). For the water desorption method, a saturated sample is drained stepwise and the water volume that is removed from the soil pores is measured, which enables porosity to be determined. Other methods are based on nuclear techniques, such as gamma-ray attenuation or computed tomography following the Beer-Lambert Law, where a gamma- or X-ray interacts with a material and the absorbed intensity of the gamma- or X-ray is transmitted (Pires and Pereira, 2014).

Since in-situ measurements of porosity in the field and in the laboratory are time- and labor-intensive, several theoretical or mathematical equations have been developed to estimate porosity. Most of the mathematical predictors (Table 1) apply empirical relationships between porosity and the grain size distribution, where other controlling factors like grain shape, for example, are neglected (Frings et al., 2011). For these predictors, two approaches are available. The first uses the D_{50} as the characteristic parameter, while the second approach is based predominantly on the geometric standard deviation. Komura (1961) first established a relationship between the D_{50} and porosity using unconsolidated natural sediments from different Japanese rivers. The equation of Carling and Reader (1982) also employs a correlation ($r^2 = 0.9$; $p < 0.001$) between the D_{50} and the porosity of poorly sorted, unconsolidated sediments. Wu and Wang (2006) used data based on studies found in the literature and data from different reservoirs in China (see Chinese Association of Hydraulic Engineering CAHE, Committee on Sedimentation, 1992). By modifying and adapting the approach of Komura (1963), a correlation with the D_{50} can be confirmed. The second approach uses the geometric standard deviation σ_G, which considers the whole grain size distribution instead of only one statistical parameter. The geometric standard deviation σ_G of the φ-scale is calculated via the method of moments (Frings et al., 2011):

$$\sigma_G = \sqrt{\sum f_i \left(\varphi_i - \sum f_i \varphi_i\right)^2} \qquad (2)$$

where f_i is the fraction of sediments in size class i and φ_i is the characteristic sediment diameter for size class i, expressed on the φ-scale. Wooster et al. (2008) established a relation between the geometric standard deviation and the porosity using a power function ($r^2 = 0.85$, $p < 0.001$). Frings et al. (2011) measured the porosity of sediment mixtures based on samples obtained from the field and the laboratory and established a multivariate regression function between the geometric standard deviation, the percentage of fines smaller than 0.5 mm ($f_{<0.5}$) and the porosity ($r^2 = 0.71$). Beside mathematical predictors based on the grain size distribution, Yu and Standish (1991) established a linear-mixture packing model to estimate the porosity. Liang et al. (2015) developed a stochastic digital packing algorithm that considers controlling factors such as grain shape. Table 1 summarizes the mathematical predictors mentioned above, which are based on a relationship between porosity and the grain size distribution. Although mathematical predictors are easy to apply, it is widely recognized that they do not reproduce porosity very accurately (Frings et al. 2011), making direct measurements of porosity desirable.

The objective of this study is to develop a new approach to measure the porosity of sediment samples using the photogrammetric technique Structure-from-Motion with Multi View Stereo (SfM-MVS). SfM-MVS requires multiple overlapping photographs of an object from different perspectives (multiple viewpoints) to resolve a three-dimensional model of the object (e.g., Westoby et al., 2012). In this study, it is applied to determine volumes of frozen sediment samples for further assessment of porosity. Using the SfM-MVS method, only the acquisition of sufficient digital images is required in the field. To investigate the capability of SfM for porosity measurements, we (i) determined the accuracy of volume measurements for simple geometric bodies with known geometry, (ii) identified the overall accuracy of porosity measurements for various homogeneous sediments, artificially mixed sediments, and natural sediment samples, and (iii) compared the measured porosity values with porosity values calculated from mathematical predictors in literature and evaluated the general performance of mathematical predictors. The volumes and porosities obtained in (i) and (ii) were also compared to the most commonly applied water replacement method (WRM).

2. Materials and methods

2.1. Principles of SfM-MVS photogrammetry

SfM-MVS photogrammetry can be performed with consumer-grade cameras, requires no expert supervision (Micheletti et al., 2015), and is therefore extensively employed in various fields of application (Westoby et al., 2012; Eltner et al., 2016; Smith et al., 2015). Eltner et al. (2016) provides an overview of the merits and limits of SfM-MVS, including different fields of application such as the generation of digital elevation models (DEM) with unmanned airborne vehicles (UAV).

SfM-MVS differs from traditional stereoscopic photogrammetry in that it automatically computes camera position and orientation (Snavely et al., 2008; Westoby et al., 2012). Overall, five steps are necessary to produce a high quality 3D model of an object or surface during the processing of digital images. First, high-resolution images must be acquired with sufficient overlap to generate a high-quality model. Second, the software detects features on overlapping images, which are invariant to scaling and rotation effects (e.g., Westoby et al., 2012). With a scale invariant feature transformation (SIFT, Lowe, 1999), the spatial relationship between the image location in a coordinate system is established (Micheletti et al., 2015). These ‘key points’ are detected for all images and are used to determine the exact camera position. A sparse point cloud (Fig. 1a) consisting of tie points (points that tie one image to another) is created out of the key points by a sparse bundle adjustment (Snavely et al., 2008), resulting in their 3D location (Micheletti et al., 2015). In the third step, the sparse cloud is intensified by applying Multi View Stereo techniques (MVS, e.g., Furukawa and Ponce, 2010; Westoby et al., 2012; Micheletti et al., 2015), resulting in the dense

Table 1
Mathematical predictors to estimate porosity based on a relationship between porosity and grain size.

Reference	Equation	Range of application
Komura (1961)	$n = 0.0864 D_{50}^{-0.21} + 0.245$ (D_{50} in cm)	$0.01 < D_{50} < 1000$ mm
Carling and Reader (1982)	$n = 0.4665 D_{50}^{-0.21} - 0.0333$	D = 2–1000 mm $5 < D_{50} < 200$ mm
Wu and Wang (2006)	$n = 0.13 + \frac{0.21}{(D_{50}+0.002)^{0.21}}$	$10^{-3} < D_{50} < 100$ mm
Wooster et al. (2008)	$n = 0.621 \sigma_G^{-0.659}$	D = 0.075–22 mm $0.26 < \sigma_G < 1.80$
Frings et al. (2011)	$n = 0.353 - 0.068\sigma_G + 0.219 f_{<0.5}$	D = 0.02–125 mm