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Identifying individual rocks within laser scans for a rigorous deformation analysis of water dams

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ABSTRACT

Water dams are an important infrastructure component for energy generation, water supply and flood control. Regular inspections of the structures for damage and deformation are necessary for safe operation and to ensure stability. In addition to the traditional concepts of geodetic network measurement, laser scan data can be used to deliver areal information on deformation. Within this topic, we aim at developing a method that identifies individual rocks of dam walls within the laser scans to introduce them as identical feature points for a rigorous deformation analysis. For this purpose, it is necessary to identify the solid stone surfaces on the water dams from scan data, and separated them from vegetation and joints. In this paper, we investigate method for identification of individual stones on gravity dams made of rubble stones. For the segmentation, the intensity values, RGB color information and local geometric structure from textured point clouds acquired with Terrestrial Laser Scanners are investigated. The classification should be robust against outer measurement conditions and provide sharp object boundaries. Our results show that – although many different methods are available – a reliable classification of single rubble stones is still a challenge task.

I. INTRODUCTION

In today's society, dams and barrages have become indispensable infrastructure components with a wide range of benefits. Among other things, they make an important contribution to the generation of electrical energy, ensure the water supply for the population (both as drinking water and as water for agriculture) and enable waterways to be made navigable. They are also an important component of flood protection and flood management. Finally yet importantly, they also play an important role in the field of leisure and tourism (BMU / UBA, 2017).

According to the international dam register of International Commission On Large Dams (ICOLD), there are 371 large dams in Germany alone (Deutsches Talsperren Komitee e. V., 2013). The category of "large dams" includes dams if either the height of the dam structure from the lowest point of the foundation to the top of the structure is 15 m or more, or in the case of smaller dam structures (height between 5 m and 15 m), the dam capacity is more than 3 million cubic meters of water. In addition to those large dams, there are a very large number of smaller structures such as dams and reservoirs, retention basin basins.

In order to guarantee the safe operation and stability of these structures, these dams and reservoirs must undergo regular inspections and monitoring measurements. In addition to permanent sensors such as plumb bobs, inclinometers, extensometers, joint gap measurements, strain gauges, pressure gauges, seepage water measuring points, etc., which are permanently installed in the dam, these also include geodetic measuring methods. Here, traditionally, levelling, tacheometric measurements and GNSS networks are used to build up a geodetic measurement network (Möser *et al*., 2013). Even if those networks are highly accurate and allow a rigorous deformation analysis with statistical determined statements on significance of changes between the epochs, they have one big disadvantage: the low number of control point. Thus, a deformation of the structure is only be detectable if on measurement point is representative for the deformation (generalization problem). Deformations that occur between the individual points of the monitoring network cannot be detected and might be overlooked or can only be detected proportionally (Pelzer, 1985).

To overcome those gaps in the monitoring networks, different measuring procedures and methods for an aerial deformation monitoring are investigated and under development for several years. In addition to remote sensing methods (*e.g*., Milillo *et al*., 2016; or Di Martire *et al*., 2014), ground-based SAR (*e.g*. Scaioni *et al*., 2018; or Huang *et al*., 2017), and purely photogrammetric approaches (*e.g*. Buffi *et al*., 2017), 3D terrestrial laser scanning (TLS) have become established in engineering geodesy for areal detection of deformations on dams (see Section I A). The advanced technology of 3D scanners hardware allows nowadays – even objects in the size of a dam wall - to be captured very accurately and in a short time. Beside a dense point cloud, image information (RGB) and the intensity of the reflected laser point can be acquired.

The obtained 3D point clouds can then be examined for deformations.

The following Section I A provides a brief overview of common deformation analysis methods, and in Section I B, the targeted approach for a feature-based method for shallow deformation analysis of dams with rubble stone surface.

A. *Deformation monitoring with TLS point clouds*

For the derivation of areal deformations from TLS point clouds, different methods have been developed in recent years and have been verify on dam structures. The methods can be divided in five classes (Ohlmann-Lauber and Schäfer, 2011): "point based strategies" (*e.g*. Schäfer *et al*., 2004), "point cloud based methods", "surface based methods" (*e.g*. Alba *et al*., 2006), "geometry based methods" (*e.g*. Grimm-Pitzinger and Rudig, 2005) or González-Aguilera *et al*. (2008), and "parameter based procedures" (*e.g*. Eling, 2009).

For natural objects whose exact target geometry is unknown, mostly point cloud-based methods or surface based methods are used, *i.e*. cloud-to-cloud, cloud-to-mash or model-to-model computation methods are used to derive the distances between two point clouds. Some of these methods have already been performed on dams (compare Holst *et al*., 2017a & Holst *et al*., 2017b).

The results of that deformation analysis are usually color-coded point clouds or vector fields, which are supposed to illustrate the deformation. However, these methods of calculating and illustrating deformations are challenging to interpret and have the disadvantage, that no statistical analysis of the results for significance can be performed precisely because a lack of identical points and unknown stochastic accuracy models of the laser scanners (Wunderlich *et al*., 2016). Due to the system, slightly different object points are appropriate at each epoch in TLS, so that no direct point-to-point assignment between individual scans is possible, as in classical network measurements. Additionally, due to the lack of identical points, those methods are not sensitive to in-plain-movements and are most sensitive to movements in line of site of the laser scanner.

Likewise, iterative closest point (ICP) based approaches can be used for deformation monitoring (Chmelina *et al*., 2012; Wujanz *et al*., 2014). Here, small patches of the point clouds are matched between the individual temporal epochs. The determined transformation parameters can then be used to infer any deformations. Due to the low sensitivity for in-plane movements and the danger of snapping into local minimums, the ICP method is not suitable for all objects, depending on their shape and the expected class of deformations (rigid body movement or shape change).

Another point cloud based method for deformation monitoring is identifying identical (artificially) points, described with a feature vector derived from the point clouds (for example 3D-SIFT, Scovanner *et al*., 2007; FPFH, Rusu *et al*. ,2009; or learned features, Deng *et al*., 2018; Gojcic *et al*., 2019). That feature descriptors can be matched between different monitoring epochs and a deformation vector can be directly calculated by the differences of the feature key points.

B. *Aim of this work*

Because dams have to undergo regular monitoring measurements to ensure their stability, it is worthwhile to look for automatable solutions for an areal deformation analysis. In order not to miss t movements perpendicular to the surface of the structure, a feature-based deformation analysis method should be developed. As revealed in our previous research on feature-based deformation monitoring (Wiedemann *et al*., 2017), the extraction and matching of feature descripts proves to be difficult on a global level. Thus, we aim to reduce the search space for identical points on the object.

In our case study with two water dams clad with rubble stones (see Section II), we plan to generate a stone cadaster as proposed in Holst (2019), clustering a bounded subset of points for every single stone, as a first step towards a feature-based deformation monitoring. The regions of the different stones should be segmented automatically from the RGB-colored TLS point clouds. This pre-segmentation of solid stone faces, as regions where a pure rigid body motion and no shape change is expected, helps to reduce the search space and lead to more stable feature descriptors. It is also intended to avoid incorrect assignments during the feature matching and time-consuming filtering of those outliers. Depending on which feature type is selected for the subsequent deformation analysis - here, for example, the center of gravity of the object, the point of the strongest curvature, etc. could be used - the segmentation must be carried out reliably and with clear object boundaries. In order to achieve this, the first step is to label the individual points of the point cloud according to their object type. Subsequently, in a second step, the classified points need to be merged into groups of points of individual stones.

In the following, different possibilities and approaches for the classification and point labeling process for 3D point clouds are discussed and evaluated for their suitability based on the collected measurement data.

II. OBJECT OF INVESTIGATION & MEASUREMENT DATA

For our analysis, the point clouds of two water dams - the Brucher dam and the Jubach dam, both in the state of North Rhine-Westphalia, Germany - were scanned. The investigated structures are gravity dams, which are clad with rubble stones (greywacke stones) on the air side (see. Figure 1). The crown length is about 200 m for the Brucher dam and 140 m for the Jubach dam, with a maximum height of approximately 25 m both.

Figure 1. Impression of the Jubach dam, showing the challenging weather conditions.

The two investigated objects are a widely spread construction form of gravity dams in Germany. Many of these walls go back to the civil engineer Prof. Otto Intze, who built more than 40 dams of the same or similar design at the turn of the 20th century, of which most are still in operation today.

The walls have a ~2 m high vertical part under the dams crown, and then spread to its base in a slight curve, leading to a inclination of ~55° - 65° at the food of the wall. These quite flat lower parts, are strongly exposed to rain and favors the growth of vegetation in the form of moss, grass and even small bushes.

The rubble stones, which are mostly only roughly hewn, show almost natural structures on their surface and are connected with grout joints. The stones vary in size, shape and color over the scenes. The masonry wall also does not have a clear topology. The bricks can both protrude from the mortar joints, and come to lie behind them (see Figure 2). The joint width also varies in size structure and color.

The point cloud of the dams are taken under ordinary realistic conditions (foggy weather and drizzling rain) using a Leica ScanStation P50 with high spatial resolution (1.6 mm@10 m) from one station approximately in the center of each the wall. Thus, the resolution of the point cloud on the dam surface is approximately 3.5 mm in the center of the wall (closest range to the scanner) and approximately 14 mm in the outer areas. During data acquisition, panoramic images are captured with the scanner's integrated camera system to texture the point clouds with RGB color (see Figure 3).

Figure 2. Challenging structure for geometric features as stone and joins have very similar surface characteristics and no clear topology.

III. Investigation of different classification methods

As mentioned above, the aim of this work is to separate as much solid rock areas on the wall as possible from the disturbing background, such as joints, vegetation or other attachments. For the segmentation procedure, there are essentially two different types of information available in the point clouds:

A. Radiometric information.
B. Geometric information.

These two types of information will now be examined in more detail and analyzed how they can contribute to robust segmentation of single stone surfaces in the 3D point clouds.

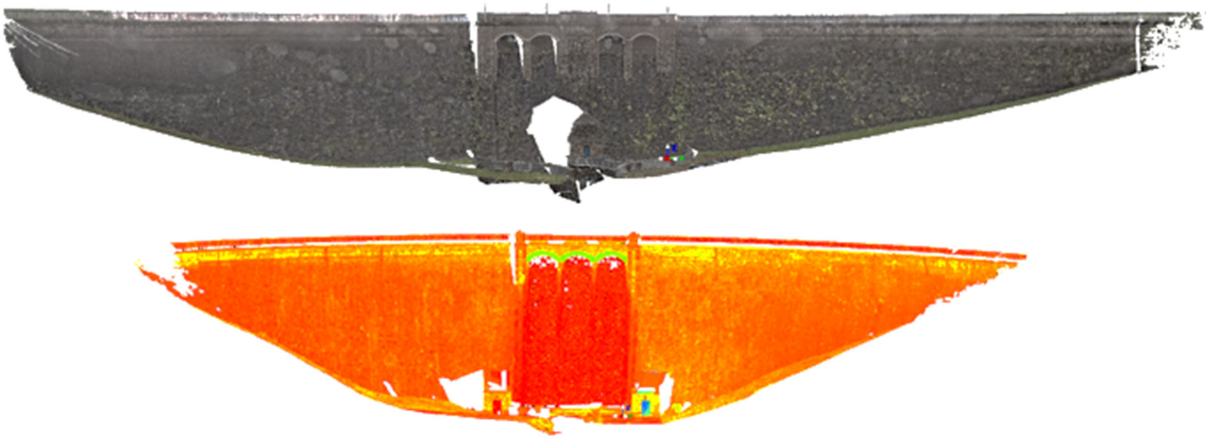

Figure 3. RGB-colored point cloud of Burcher dam (top), point cloud colored by raw intensities of Jubach dam (bottom).

A. *Radiometric information*

Laser scanners provide not only the 3D coordinates of the point cloud, but also radiometric information to the user. In general, the intensity of each reflected laser spot is recorded during the measurement. As the used scanner is equipped with an internal camera, also color information from panoramic images can be projected to the point cloud without shadowing or parallax effects. Therefore, every point has additional RGB color information.

1) Intensity-Information: As stated above, modern laser scanners store an intensity value in addition to the measured coordinates for every point. The intensity indicates how much of the emitted laser light is reflected from the object back to the laser scanner and detected. The raw intensities depend on the material properties, the color and the surface structure of the object, as well as the angle of incidence of the laser beam, the measuring distance and the laser wavelength used (Wujanz *et al*., 2018).

A previous work as shown, that in certain parts of the wall, with a distinct joint pattern, regular structure and a dry wall condition, stones can be segmented using intensity values. For that in Steffens (2020), the k-mean algorithm (Lloyd, 1982) is used to divide the point cloud into two classes based on their intensity. In a further step, the DBSCAN algorithm (Ester *et al*., 1996) is used to cluster the points labeled as stone to groups of individual stones segments.

With this method, precision values of ~80-95 % can be achieved (percentage of points classified as stone, which are also stones in reality). However, only recall values (number of real stones which are identified by the algorithm) of ~49-70 % are achieved (compare Steffens, 2020).

Similar approaches performed by us show that the accuracy of the segmentation based on the intensity values decreases rapidly if the wall is not scanned under optimal conditions. In particular, moisture on the wall will worsens the result. This is mainly attributed due to the wavelength of the laser scanner used. The Leica ScanStation P50 – like most other TLS systems – uses a laser source in the near infrared spectrum (often 1550 nm) as they are usually eye-safe. However, laser light in the near infrared spectrum is highly absorbed by water, so that the intensity is strongly reduced by humidity or accumulating wetness on the wall (Wojtanowski *et al*., 2014). As a result, objects that show differences in intensity in dry state, have an almost identical, very low intensity value when they are wet (see Figure 4).

As a result, in this case study dataset, a segmentation by intensity is only possible in a small dry part of the dam. On the wet parts, an assignment of the categories "stone" or "joint" by the k-mean algorithm is no longer possible, even if the class boundaries are adjusted to the local environment. The variation in intensity between is too small to distinguish the two object classes precisely (see Figure 5). Small-scale changes in intensity are more likely to be linked to differences in the incident angle of the laser beam or the humidity, and cannot be attributed to the structural characteristics of the wall.

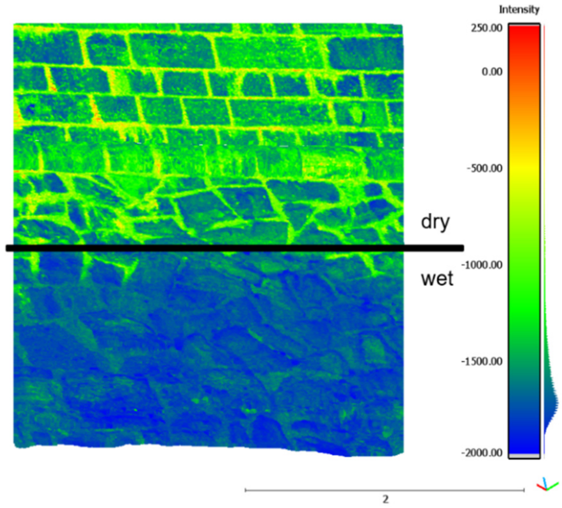

Figure 4. Distribution of intensity values: dry upper part and lower wet part of the wall.

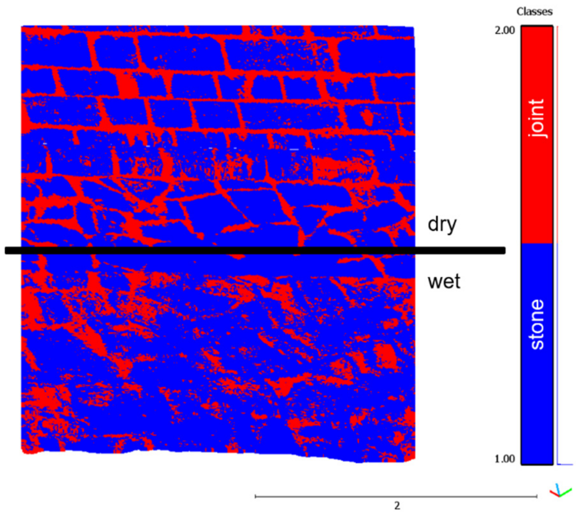

Figure 5. Results of the k-mean classification based on the intensity: acceptable results in try areas (upper part) and Insufficient results wet parts (lower part) of the dam.

2) RGB-Information: For a classification with respect to the RGB colors, or gray scale images derived from them, a wide range of functions from the image processing domain can be used (Gauch and Hsia, 1992; Valero *et al*., 2018; Wang *et al*., 2014) for 2D images. These images can be obtained from the raw camera data of the scanner, or by projecting the RGB values of point cloud onto an artificial image plane. After a classification, the derived classes must then be projected back into the point clouds to generate labels for the individual points. For a segmentation directly in the 3D point cloud, color-based region-growing algorithms can be applied (Zhana *et al*., 2009).

In general, RGB segmentation is a promising method for scenes wherein the object's color differs significantly from the background. For our outdoor scenes, this does not apply. A closer look to the color information reveals the following: Firstly, the colors of the stone surface and the joints are very similar, so that no general color value can be assigned to the different object classes. Secondly, local color changes are often not lined up with the structural characteristic, but are more related to the current illumination conditions, shadowing effects and the state (dry/wet) of the local surface. Also, mineral efflorescence disturb the color pattern In summary, it cannot be assumed that the color information can contribute to a reliable segmentation (see Figure 6).

Figure 6. Typical section of the RGB textured point cloud. Only slight differences between joint and stones are visible, mineral efflorescence disturbs the joint pattern.

In addition, several general disadvantages must be taken into account for this kind of information. As a passive sensor captures the RGB information, the color impression and brightness is highly depending on current external illumination condition.

B. *Geometric information*

Geometric statements about the local structure of the point cloud can calculated by observing the neighborhoods of a core point. Such derived geometric features can be for example the linearity, planarity, curvature, point density, roughness, normal direction, omnivariance, spherically, eigenentropy, etc. and are well described in the literature (*e.g.* Weinmann *et al.*, 2014; or Hackel *et al.*, 2016). Such features can serve as input for a subsequent classification if the object classes can be separated in the feature space.

Methods proposed in the literature (specifically Brodu and Lague, 2012, CANUPO-algorithm and Weinmann *et al.*, 2017) for a proper selection of neighborhood size, for feature calculation and the assessment of relevant features, haven not provided meaningful results in this case study. Other supervised classification methods like SVM, nearest neighbor, and design trees – which can be trained with the Matlab classification toolbox by manual labeled data – do not provide clear class assignment to the precisely calculated geometrical features. A closer look to distribution of the calculated geometrical features show, that they are very similar for both object classes 'stone' and 'joint' (see Figure 7).

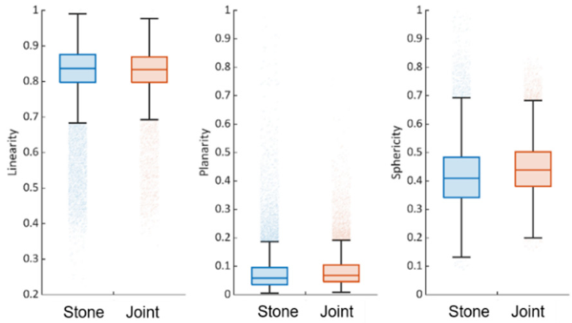

Figure 7. Three exemplary geometrical features (linearity, planarity, spherically (left to right)) showing very similar distributions for both object classes (stone/joint).

The unfavorable combination of the low resolution of the point cloud relative to a very little surface change, the unclear topology between joints and stones (see Figure 3) cause that the determined geometric descriptors cannot be reliably assigned to the object classes.

A different approach based on the use of local geometry can be applied, if the objects to be segmented are distinct clearly from the background. Then, the computed distance of the point cloud to a previously estimated control geometry can be used for segmentation (see Figure 8). In this case study, this procedure is suitable in the upper part of the dam, which is very evenly masoned and has clearly separated of individual stones by joints (see Figure 8).

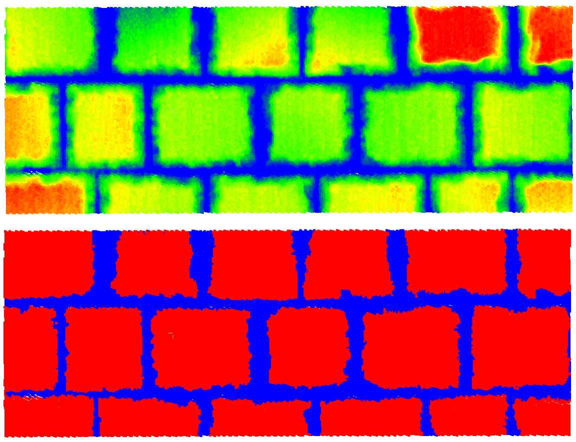

Figure 8. Depth map for segmentation- top: depth map, bottom: segmentation result with threshold method.

Using a best-fit plane as a reference geometry, a depth map can be obtained by calculating the perpendicular distance between the point cloud and the plane. For the segmentation of the stones in this area, a simple threshold method for the reliable segmentation is sufficient. Since the dam is curved along its longitudinal axis, only the estimation of the plane must be continuously adjusted.

However, in regions where the stones do not stick out above the joints, this method fails completely. Likewise, vegetation, which protrudes above the wall, is added to the class stone.

For fixed geometries, *e.g*. planes, also region growing methods can be used (Ötsch, 2021). In this case, the adjacent points are added to a seed point until a threshold value for a local geometric descriptor is exceeded. Due to the irregular stone shapes and the uneven surfaces, this method cannot be used successfully at the investigated dams.

IV. Conclusion

As a pre-segmentation of a follow-up feature-based deformation analysis, the surfaces of individual stones should be identified in the point clouds of rubble stone water dams. This should simplify the calculation of the final features and stabilize the matching. In this case study, different segmentation methods were investigated on the TLS point clouds of two water dams built of rubble stones, which were scanned under challenging weather conditions. In this point clouds, all included information types – RGB colors, intensity and the intrinsic geometry of the point cloud – were examined for their suitability for a segmentation approach.

We found, that under challenging, but ordinary weather conditions with wet object surfaces, radiometric information can only contribute to the segmentation to a limited extent. On the mostly wet surface, differences in RGB color and intensity are too low to distinguish between solid stone faces from other objects reliable. In dry areas, a classification based on intensity values seems a promising strategy but is often interfered by efflorescence of the joint material leading misclassification in these areas.

The two investigated classification methods based on the point clouds geometries show different results at our test sides. The feature-based approach fails because the complicated, unstructured wall offers too few distinguishable geometrical characteristics between stones and joints. This is mainly due to the distance-related poor resolution of the point clouds in comparison with the little surface undulations. Thus, the distribution of the feature values are practically identical in the hole point cloud. However, segmentation results from locally computed depth maps with respect to best fitting geometries are suitable for well-structured parts of the scanned wall, even if in large part the complicated structural shape of the walls surface also prevents this classification approach.

In summary, the data we have collected show that the investigated segmentation procedures described in the literature are not sufficient to perform a reliable segmentation in all areas of the investigated rubble stone dames.

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