An Approach to 3D Digitisation and Segmentation of the Interior and Exterior of a Complex Museum Object

Simon Albers[1], Thomas Luhmann[1], Till Sieberth[1]

[1]Institute for Applied Photogrammetry and Geoinformatics, Jade University of Applied Sciences, Oldenburg, Germany
(simon.albers, luhmann, till.sieberth)@jade-hs.de

Keywords: Cultural Heritage, Digitisation, Segmentation, Low-Cost.

Abstract

The digitisation of cultural heritage objects is an important procedure to conserve, share and analyse artefacts from the past. Nowadays, it is common practice to digitise artefacts using DSLR cameras and Structure from Motion. For most objects, this is a suitable procedure, but in some cases, objects have narrow interiors which cannot be reached with common camera equipment. Our case study is a small kayak model (~ 1 x 0.1 x 0.15 m) from the 19th century with an interior that can only be documented through small openings (0.1 m radius). We developed a method using a modified webcam to safely digitise the interior of the kayak. By comparing three datasets of a test object, we describe advantages and disadvantages of the usage of integrated autofocus and colour balance of the webcam. Furthermore, we extended our approach for segmentation of 3D models to consider the interior and prepare the models for future analysis. There were no major differences between the models of the three datasets, and all of them could reduce the data gaps in the 3D model based on the DSLR images noticeably.

1. Introduction

An important aspect of cultural heritage are tangible objects in museums and similar institutions. These objects are always at risk of being stolen, or destroyed by disasters, accidents or natural decay. Furthermore, physical objects are often unique and bound to a specific place. Three-dimensional models provide a practical backup for cultural heritage objects in the event of destruction, and also enable them to be shared quickly and widely via the internet (Kantaros et al., 2023). However, these objects are highly diverse, and therefore, the digitisation is not always straightforward. Some of them can be 3D digitised comparably easy using common techniques of optical 3D measurement, such as Structure from Motion (SfM). Others need specified tools to capture the whole object. One challenge can be narrow interiors, which cannot be captured with commonly used DSLR cameras. In our case study, we want to digitise the interior of a kayak model with a length of around one meter that can be reached through three openings with a diameter of around 10 cm. To solve this challenge, we developed a measuring setup consisting of a webcam with integrated lighting, a custom mount and a tripod. To improve the image quality, the webcam uses an autofocus and automatic colour balance by default. This is especially important at very close distances because focus settings are critical due to the very limited depth of field (Luhmann et al., 2023). For the evaluation of our measuring setup, we constructed a test object that simulates the measurement conditions. This way, we have easier access to the object and do not risk damaging the museum object during the experiments. We compare three datasets with different combinations regarding the settings for the autofocus and the automatic colour balance, and analyse the produced 3D models regarding their geometry. While the autofocus is used for the first dataset, the focus is manually set to a fixed value for the other two datasets. The automatic colour balance is only used for the first and third datasets.

A 3D model alone can support research in the field of cultural heritage, but for more in-depth analysis, additional information should be connected to the bare 3D geometry. One way is the segmentation of these models to define and label important parts, as well as simplify the handling of the models by interactively choosing only a subsample of the parts. Furthermore, the segmentation enables new analysis, such as the description of the relation between the segments or the comparison of objects. Thereby, the consideration of interior structures is an additional challenge.

The main contributions in this paper are:

- The development of a measuring setup to safely digitise the interior of fragile cultural heritage objects.
- A comparison of different datasets and settings to evaluate the geometry of the produced 3D models.
- An extension for the segmentation of the exterior and interior of 3D models.

This work is part of the DiViAS project (“Digitisation, Visualisation and Analysis of Collection Items”). The research network combines domain knowledge from the field of history and cultural studies with technology and computer science to extend the way written sources and cultural heritage objects are analysed. In the first case study, information from digitised logbooks is extracted using Natural Language Processing and Named Entity Recognition. In the second case study, 3D models of cultural heritage objects are created using 3D optical measurement methods. These models are used to get in touch with potential societies of origin and further analysis (DiViAS, 2026; Luhmann et al., 2026).

The rest of the paper is outlined as follows: Section 2 presents related work regarding the 3D digitisation of cultural heritage and the segmentation of 3D models. In Section 3, we describe our case study and the developed test object. Furthermore, we present our measuring setup, the created datasets and the segmentation approach in Section 4. Next, we compare the results of the three datasets and show the segmentation of both objects in Section 5. After we discussed our results in Section 6, the paper concludes with ideas for further research.

2. Related Work

The 3D digitisation of cultural heritage objects is an ongoing research topic, combining expertise from the field of museum studies and three-dimensional measurement technologies. 3D representations created using techniques such as SfM or laser scanning provide a holistic view of artefacts and collections that can be used as a tool for the conservation and (virtual) restoration of objects. Apollonio et al. (2021) describe a low-cost workflow based on SfM for the digitisation of museum objects aimed at small to medium-sized institutions. They used smartphone cameras with image preprocessing and colour correction to generate high-quality models and derived models with low resolution for different use cases. They aimed to create a fast and low-cost workflow based on mobile and affordable equipment.

In their work, Apollonio et al. (2021) focused on objects that are comparable easy to digitise. The workflow is suitable for a high number of objects, but does not consider uncommon challenges, such as the digitisation of object interiors.

Zhan et al. (2021), who are working on the digitisation of historic gyroscopes from a collection at the University of Stuttgart, use an endoscope in combination with computed tomography (CT) and a DSLR camera. First, they create three individual reconstructions based on the three data acquisition devices. Subsequently, they register the model from the endoscope with the model from the DSLR camera using homologous points and a Gauss-Helmert model. One of the main challenges is to guarantee a sufficient overlap between the images from the endoscope for the 3D reconstruction using SfM. Besides that, there are challenges regarding the camera calibration, the image preprocessing and the general optimisation of the SfM workflow.

In our case, CT is not a valid option because the risk of damaging the object during transportation is too high, and bringing a CT into the museum is very expensive. Furthermore, the visibility of different materials in CT is dependent on the used radiant energy. Especially without knowledge about the interior material, choosing the right energy and settings is a complex task (Heckert et al., 2020; Götz et al., 2025). Therefore, we restrict ourselves to methods applicable at the museum and in consideration of the possibilities usually available in a museum. This results in the requirement of a low-cost, easy-to-apply workflow. As guiding an endoscope through a narrow interior is not trivial, we developed a measuring setup that is less flexible in its movement, but therefore safer to use.

However, 3D digitisation by itself only creates virtual copies, representing the visual appearance by approximating the geometry and colours of an object. The digitisation of an object does not record further semantic or physical information, such as the materiality. To consider this information, they must be added afterwards based on additional measurements or expert knowledge. However, an object can consist of multiple parts or materials and, therefore, must be divided into segments with similar attributes first. This kind of semantic segmentation of 3D data is a widely discussed topic and supports humans and machines to understand scenes and objects (Yang et al., 2023; He et al., 2025). For the segmentation, handcrafted features or techniques from the field of deep learning can be used. An established tool for the segmentation of point clouds is the neural network PointNet by Qi et al. (2016) that can be trained for different tasks like classification, semantic segmentation and part segmentation. Huge datasets of labelled point clouds are needed for the training, which are missing in the field of cultural heritage objects. Alternatively, so-called zero-shot models can be applied, which are highly generalised and suitable for a wide range of tasks, even without dedicated training data from the area of use. An example of such a model for the segmentation of images is the Segment Anything Model (SAM) by Meta (California, United States of America). SAM is trained with eleven million images and one billion masks and segments images based on user inputs such as text prompts or image coordinates, or fully automatically (Kirillov et al., 2023). While SAM can only be used with 2D image data, there are approaches that transfer the segments to 3D models, such as PartSlip++ and SAMPart3D. PartSlip++ by Zhou et al. (2023) creates synthetic images of 3D models, detects parts by using text prompts and uses SAM to get fine masks of the parts based on bounding boxes. SAMPart3D by Yang et al. (2024) combines 3D features and 2D masks for the segmentation of synthetic 3D models and includes a Multimodal Large Language Model to generate labels.

Using text prompts in the field of cultural heritage objects can be complicated, because the objects are highly diverse and their parts may not have a distinct description. Furthermore, the existing approaches do not consider potential interior of the objects. In our use case, the interior is an essential part of the object and therefore cannot be ignored.

3. Materials

In our case study, we digitise a kayak model from the so-called Kuprejanov collection (Figure 1). Ivan Antonovič Kuprejanov (assumed 1794-1857) was a naval officer and governor of Russian America, today’s Alaska, between 1835 and 1840 (König, 1993). He collected authentic objects from the indigenous people, such as tools, weapons and ritual artefacts, as well as natural objects. The collection includes 137 objects which are rich in different materials like wood, stone, leather and shells (Bucher, 2009). Later, part of the collection was transferred to Germany. One part of this collection is a kayak made of a leather covering and a wooden frame on the inside. The kayak has a length of just over 1 m, and the inside can be reached through three openings, each with a diameter of around 10 cm.

Figure 1. Kayak model artefact.

Besides the real cultural heritage object, we use a self-built test object (Figure 2) for easier access and therefore a faster evaluation without the risk of damaging the kayak during our experiments. Furthermore, we can open our test object to compare different data acquisition methods. The test object has three openings, each with a diameter of around 10 cm. The bottom is covered with a wooden framework. Some markers are attached to the rims of the openings, the bottom and the inner sides. Additional strips with random textures are added to the sides. Initially, we used all three openings, but then the images from the DSLR camera were sufficient to capture the interior. The openings of the kayak are further apart than those of the test object, which seems to affect the coverage more than expected. That is why we covered the middle opening in our experiments to get a distinct part of the interior that cannot be captured from the outside while the cover is closed.

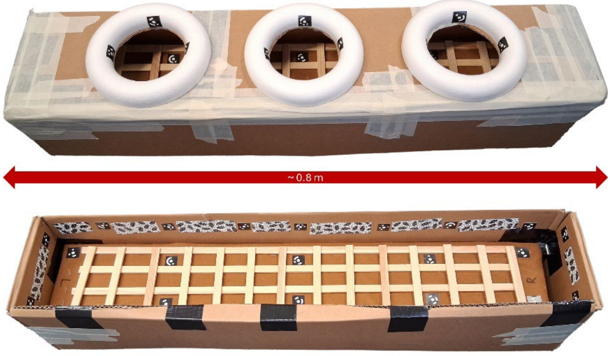


Figure 2. Test object from the outside (top) and the inside (bottom).

4. Method

Our measuring setup consists of a modified webcam and a tripod. We used it to capture the interior of the test object with different settings in regard to the autofocus and the colour balance. Although these functions usually should be avoided due to changes in interior orientation and colour impression, we investigate the impact on the 3D model accuracy to evaluate a best practice for similar scenarios. Three datasets and the comparison of the generated models are described. Furthermore, we extended our approach for the segmentation of cultural heritage objects presented in Albers et al. (2026) for the interior.

4.1 Measuring Setup

The main goal of our work is to develop a system for the three-dimensional digitisation of the interior, which is easy and safe to use, portable and low-cost. A commonly used technique is SfM. While the software can be expensive in some cases, basically all kinds of image-capturing devices can be used for the data acquisition (Kingsland, 2020; Patonis, 2024). In first experiments, we used endoscopes, but due to the complexity of navigating the endoscope, we decided that the risk of touching and therefore damaging the object was too high. Additionally, the dim interior required more illumination. For those reasons, we chose a webcam with integrated lighting and developed an adapter that connects the camera to a tripod (Figure 3). This way, the camera can be safely moved vertically and rotated around its own axes. For the outside, we use a DSLR camera, which is commonly used for SfM. For a holistic representation of an object, we must fuse both datasets. In some cases, data fusion between the two types of images occurs automatically. In other cases, it is necessary to add homologous points manually.

4.2 Dataset

By default, the used webcam has an autofocus and an automatic colour balance. However, these can be altered using additional software. In most cases, it is not recommended to use an autofocus or an automatic colour balance during image acquisition for SfM. The autofocus changes the interior orientation of the camera and, therefore, treating these parameters in the calibration as constants will have a negative effect on the results (Ricolfe-Viala and Esparza, 2021). However, in this case, we see the autofocus as a possible tool for a complex problem. Depending on whether the camera is looking along the object or at one of the nearby sides, the object distance changes drastically. Without changing the principal distance manually or by using the autofocus, it is not possible to get sharp images in each direction. Similarly, the automatic colour balance will change the impression of colours in each image individually. A common colour correction method uses colour cards with cells of known colour values to calculate correction parameters based on the differences between the nominal and actual values in the image. This way, the correction parameters for the entire image sequence are calculated using a single reference image, based on the assumption that the lighting conditions and colour impression remain consistent between the images (Apollonio et al., 2021). While that is not the case when using an automatic colour balance, the changing lighting conditions and the low-cost camera heavily influence the image quality, and therefore, the colour balance is critical for visually pleasing images. To evaluate the influences of the different settings on the SfM process and the 3D models, we compare three different datasets (Table 1).

Dataset	Autofocus	Colour Balance
A	Yes	Yes
B	No	No
C	No	Yes

Table 1. The three datasets for the test object.

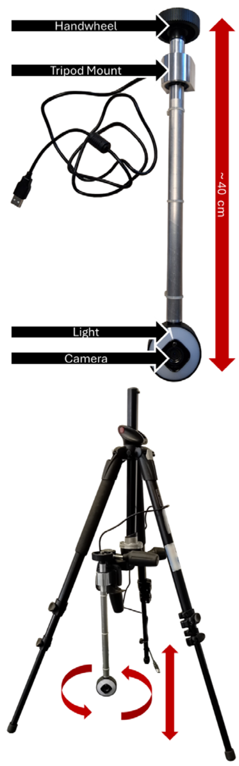


Figure 3. The webcam with lighting and the adapter (top), and the measuring setup with a tripod (bottom), the camera can be rotated and moved vertically.

4.3 Geometric Comparison

It is possible to remove the cover of the test object to capture its interior using a DSLR camera. This way, we generate a reference model using SfM with a ground sampling distance of around 0.03 mm/px and a reprojection error of around 0.8 px. Based on each dataset, we generate two 3D models: The first one is without further filtering of the tie points; the second one is filtered using the approach of Over et al. (2021) and adapted

https://doi.org/10.5194/isprs-archives-XLIX-B2-2026-779-2026 |

for cultural heritage objects by Di Filippo et al. (2022). The tie points are filtered successively by their individual reconstruction uncertainty (RU), projection accuracy (PA) and reprojection error (RE) with limits of 15, 6 and 0.3 px. The filtering is done in multiple iterations with a maximum number of removed points for the RE and PA of 50% and 10% for the RE. After each removal of tie points, the parameters must be calculated again, because they change depending on the other tie points. First experiments showed that the recommended limits for the three parameters were too low for our data, causing holes in the models. Instead, we follow the suggested procedure but with a limit of 30 for the RU, 10 for the PA and 0.6 px for the RE. Multiple iterations of removing tie points with high values are fulfilled till less than 100 points exceed the limits of each parameter.

Altogether, we compare six models regarding the number of tie points, the final reprojection error and the general covering. Additionally, we define a region of interest of the models for a more in-depth geometric analysis. This region is in the middle of the test objects and, therefore, the part that can be captured only by using the webcam. For the evaluation of the interior, we use a voxel-based approach inspired by Heeramaglore and Kolbe (2022). Our reference model is based on the DSLR images with an open cover of the test object. Using the markers in the inside as homologous points, all other models are registered to the reference. Each model is compared to the reference by counting all voxels of the reference that are also filled by each of the models created with our webcam approach. For each voxel that is not filled, the distance to the nearest filled voxel is calculated. This way, we get a coverage percentage and a mean distance with its standard deviation.

4.4 Segmentation

Our segmentation is an extension of our approach presented in Albers et al. (2026). We generate voxel models based on the 3D meshes that are used to create synthetic images from six different views (top, bottom, front, back, left, right). These images are segmented using SAM and interactively labelled by a user. After that, the labels are transferred from the images to the voxel model, smoothed and then transferred to the point cloud or the 3D mesh. Additionally, each segment can be assigned a material based on a thesaurus.

For the segmentation of the interior, different layers must be considered based on the visibility of different parts from different views. Our approach is loosely inspired by the visibility requirements presented in Alsadik et al. (2012). For each triangle of the mesh, we calculate the centroid and extract the normal. This way, we get a point cloud with points connected to individual triangles of the mesh. Using this combination of points and triangles, the layers for each view are calculated as follows (Figure 4):

1. Searching all triangles whose normal intersects the view plane, removing all other triangles.
2. Calculating the minimal viewable height (MVH), each triangle can be seen using raytracing; the MVH of triangles that are not covered are set to infinity.
3. Creating images considering the point height and the MVH so that each point is visible in at least one image, or the set limit of images is reached.

In step 3, we generate point clusters based on iteratively chosen seed points. The first seed point is the point with the minimum height in relation to the view plane. Its MVH defines the image layer. All points are added to its cluster whose heights are under the seed point's MVH and whose own MVH is the same or above the seed point's MVH. This way, we can guarantee that the points do not cover the seed point and that the points are visible from the image layer. The next seed point is the point with the minimum height that is not part of a cluster yet. This is repeated until all points are assigned to at least one cluster. For the image generation, we start with the cluster with the maximum number of points and generate images for each cluster or until the manually set limit of images is reached. These images are additionally considered in the segmentation approach mentioned above.

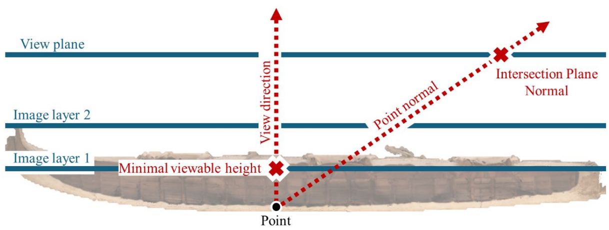


Figure 4. Schematic example of the layer process for one point.

5. Results

We evaluate our measuring setup and the described datasets quantitatively on our test object and qualitatively on the kayak. For both objects, the segmentation is visually analysed and rated.

5.1 Data Comparison

The three datasets and the six derived models are compared regarding the number of tie points, the reprojection error, and the mean distance between each voxelated model and the reference model. In Table 2, the descriptive parameters are shown. For each model, the number of tie points is reduced during the filtering process until the limits mentioned above are met. This way, the tie points are reduced by around 40% to 70%, and the reprojection error is reduced by around 0.2 to 0.6 px. The lowest reprojection error is achieved with the filtered dataset A (with autofocus and colour balance), and the highest reprojection error is seen with dataset C (without autofocus and with colour balance). The mean distance between the models and the reference is much lower for dataset A than for datasets B and C. The difference in the mean distance between the not filtered and filtered datasets is in the range of tenth of millimetres. The mean distance and the overlap consider the bottom part of the test object. The upper cover and the outer shell are ignored because they are not included in the reference data or the webcam datasets.

The distance between each voxelated model and the voxelated reference, respectively, the overlap, is visualised in Figure 5. The highest differences occur below the two openings. Depending on the dataset, the size of the areas with high differences varies. These areas are although influenced by the filtering.

This contribution has been peer-reviewed.
https://doi.org/10.5194/isprs-archives-XLIX-B2-2026-779-2026 |

Dataset	Images	Tie Points in thousands	Reprojection Error / px	Mean Distance / mm	Standard Deviation / mm	Overlap
A	258	98.6	1.17	3.5	5.6	58.5%
A*	258	56.1	0.93	3.6	5.8	58.9%
B	233	68.3	1.40	6.6	11.6	57.1%
B*	233	20.4	1.10	6.2	10.8	56.6%
C	262	80.0	1.77	7.5	11.4	48.7%
C*	262	29.6	1.17	6.9	12.2	55.9%

Table 2. Dataset with parameters. Datasets marked with * are filtered.

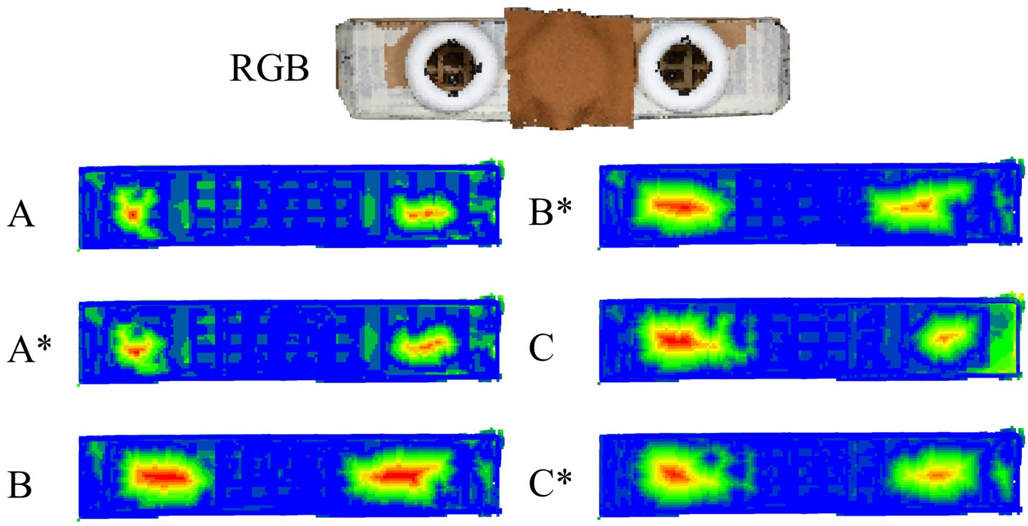


Figure 5. Top view of the voxel model of the closed test object (top) and the distance between models and reference (Blue: low; Red: high).

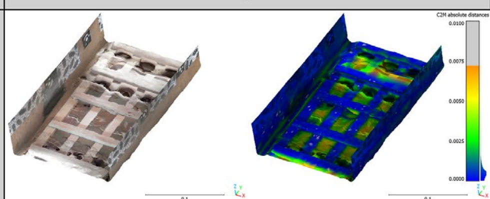
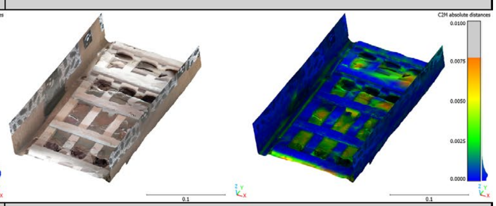
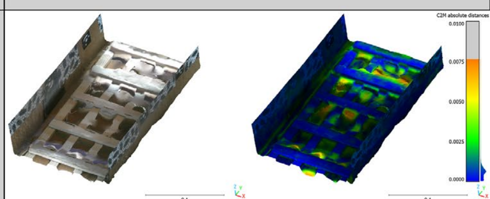
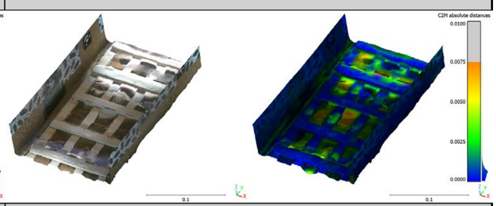
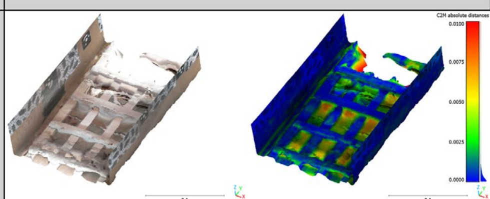
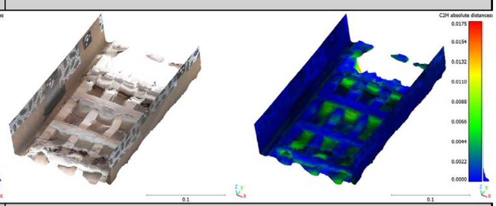
Dataset	Original	Filtered
A		
	0.702 mm / 0.713 mm	0.675 mm / 0.670 mm
B		
	0.794 mm / 0.806 mm	0.774 mm / 0.783 mm
C		
	0.73 mm / 1.081 mm	0.77 mm / 1.042 mm

Figure 6. Comparison of the datasets. RGB (left) and height to the reference (right). Mean distance between the model and the reference, and the standard deviation.

The middle section, located between the two openings, is particularly important because it can only be captured with the webcam while the cover is closed. Therefore, it is comparable to the parts of the kayak for which we have no reference. After the registration of the models, we calculate the difference between the reference and each model, without considering the direction of the difference (Figure 6). While the walls and the wooden frame show low differences, the deeper areas between the planks have higher differences compared to the reference. The mean difference to the reference is around 0.7 mm for all datasets. The standard deviation is noticeably high for dataset C. The reason for that is probably the missing data for the upper end of the considered area.

The results of the digitisation and the segmentation of the test object are shown in Figure 7. The webcam images reduce the data gap clearly, but the colour differences between the two image kinds are noticeable. Using our segmentation approach, we can segment the point cloud to capture the general structure of the object, but there are some missing details, such as missing targets and wrongly classified points (Figure 8).

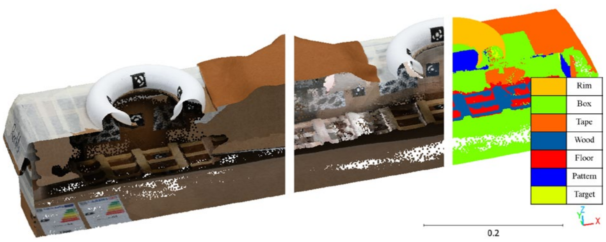


Figure 7. Point clouds of the test object: Based on DSLR images (A), webcam images (B) and segmentation (C).

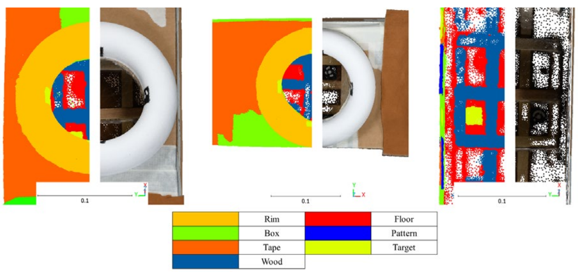


Figure 8. Examples of the segmentation of the test object.

5.2 Kayak Digitisation and Segmentation

For the digitisation of the kayak model, we use the autofocus and the automatic colour balance. Without the additional webcam images, the model of the kayak has noticeable data gaps (Figure 9). There is a colour difference between the DSLR and the webcam images. In comparison, the colours of the DSLR images are much darker, while the webcam images seem to have a higher lightness. The segmentation captures the general structure of the interior and clearly differentiates between the exterior and the interior (Figure 10). However, there are wrongly classified points, such as the incomplete frame.

6. Discussion

The effort required for data acquisition varies depending on the webcam settings. Using the autofocus and the automatic colour balance has the advantage that the corresponding parameters are chosen automatically. Depending on the lighting conditions and the scene, this can take some seconds and therefore slow down the image acquisition. However, choosing the focal distance manually can be challenging because of the varying object distances. The openings and the narrow interior limit the possible camera positions and prevent a constant object distance. Therefore, the chosen focal distance must be a compromise for the range of object distances. Furthermore, our used webcam does not provide settings for the focus and the colour balance by itself, so we had to use additional software that sometimes miscommunicated with the webcam, which slowed down the acquisition as well. Furthermore, looking at the images without automatically chosen parameters shows that the quality of the images is heavily dependent on these parameters.

Comparing the six datasets, the quality of the models is similar. The filtering reduces the reprojection error and the differences to the reference in most cases. Regarding our metrics, the filtered dataset A (with autofocus and colour balance) is the best. The reason for that could be the autofocus, which compensates for the drastically changing object distance. In combination with the comparable low-quality images, the changing focal length may not influence the reconstruction noticeably. However, there are no major differences between dataset A and the other datasets. Furthermore, some metrics could be changed by creating new datasets with the same settings but different images. In all cases, the data gaps of a model based on DSLR data alone were reduced.

In most cases, 3D digitisation can be realised using standard procedures, such as those mentioned in Apollonio et al. (2021). For more complex objects, specialised solutions with alternative equipment are needed. Examples are the usage of endoscopes (Zahn et al., 2021) or our webcam approach. The most fitting method depends on the object and the available equipment. Of course, these two approaches are not universal solutions, and for other objects, further measuring setups may be necessary.

Our segmentation approach needs more human input than comparable methods such as PartSlip++ (Zhou et al., 2023). In return, we have a more supervised workflow that incorporates human expertise and considers the interior, which is lacking in other approaches, that uses synthetic images for the segmentation of 3D models.

Figure 9. Kayak model based on the DSLR images (left) and extended by the webcam images (right).

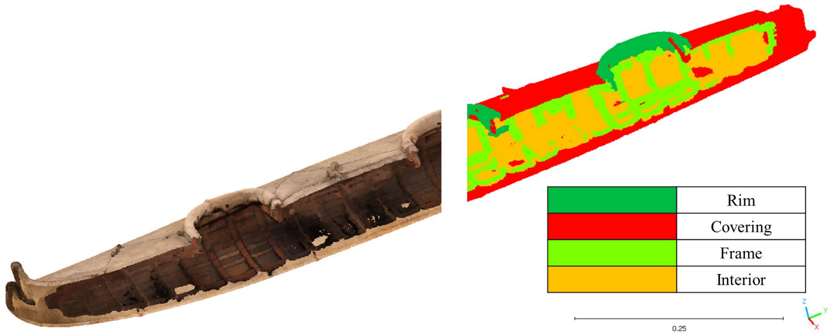


Figure 10. RGB (left) and segmented kayak model (right).

7. Conclusion and Future Work

Using our measuring setup, we can record images of areas that cannot be reached with common DSLR cameras and reduce data gaps in 3D models, thereby digitising important aspects of cultural heritage objects. While the geometric comparison does not show major differences between the datasets and all capture the general structure of the interior, the quality of the geometry and the texture based on the webcam images could be improved in the future. A possible way is to use a high-quality camera, but better hardware can be expensive and contradict the low-cost concept. Therefore, image processing to enhance the existing data may be the way to go. For example, we did first promising experiments to adjust the colour of the webcam images to the DSLR images and reduced the difference in lightness noticeably. Thereby, a more cohesive texture could be achieved.

Naturally, the quality of the segmentation is heavily influenced by the quality of the model, and therefore, a better model results in a better segmentation. At the moment, some details could be improved, but the general structure and characteristics of the object are represented in the segmentation. Based on the segmentation, we want to further describe, compare and analyse the objects to support the historical research for a better contextualisation and connection of these objects.

Acknowledgements

The authors would like to thank the whole DiViAS Team for the productive cooperation, especially the Landesmuseum Natur und Mensch Oldenburg ("State Museum Nature and Man Oldenburg") for the access to the collection and the support in handling the objects. The authors would also like to express their gratitude to the members of the IAPG for the helpful feedback and discussions. Finally, the authors want to thank Nils Sander (Jade University of Applied Sciences) for his valuable help on the construction of the webcam extension.

This work is based on the DiViAS project, funded by zukunft.niedersachsen, the joint science funding program of the Lower Saxony Ministry of Science and Culture and the Volkswagen Foundation.

References

Albers, S., Luhmann, T., Sieberth, T., 2026: Semantic segmentation for representing materiality of 3D museum artefact models. Digital Applications in Archaeology and Cultural Heritage. Submitted.

Alsadik, B.S., Gerke, M., Vosselman, G., 2012. Optimal Camera Network Design for 3D Modeling of Cultural Heritage. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. I–3, 7–12. https://doi.org/10.5194/isprsannals-I-3-7-2012.

Apollonio, F.I., Fantini, F., Garagnani, S., Gaiani, M., 2021. A Photogrammetry-Based Workflow for the Accurate 3D Construction and Visualization of Museums Assets. Remote Sensing 13, 486. https://doi.org/10.3390/rs13030486.

Bucher, G., 2009: Russisch-Amerika in deutschen Museen. In: Hermann, E., Klenke, K., Dickhardt, M. (Ed.): Form, Macht, Differenz. Göttingen: Göttingen University Press, S. 149–161.

Di Filippo, A., Antinozzi, S., Dell'Amico, A., Sanseverino, A., 2022. A Statistical Analysis for the Assessment of Close-Range Photogrammetry Geometrical Features. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLVIII-2/W2-2022, 31–38. https://doi.org/10.5194/isprs-archives-XLVIII-2-W2-2022-31-2022.

DiViAS: Digitisation, Visualisation and Analysis of Collection Items (DiViAS) [Online]. https://divias.de/en/ [last accessed: February 02, 2026].

Götz, P., Melamed, D., Bohling, H., Brovkina, C., Hussain, I., Reims, N., Junge, L., Hoffmann, D., Wiskandt, K., Schilling, R., Hering-Bertram, M., Colombi Ciacchi, L., 2025. Embedding of X-ray computed tomography data of cultural heritage objects in interactive web applications – old technical instruments brought back to novel virtual life. Journal of Cultural Heritage 76, 100–110. https://doi.org/10.1016/j.culher.2025.09.007.

He, Y., Yu, H., Liu, X., Yang, Z., Sun, W., Anwar, S., Mian, A., 2025. Deep learning based 3D segmentation in computer vision: A survey. Information Fusion 115, 102722. https://doi.org/10.1016/j.inffus.2024.102722.

Heckert, M., Enghardt, S., Bauch, J., 2020. Novel multi-energy X-ray imaging methods: Experimental results of new image processing techniques to improve material separation in computed tomography and direct radiography. PLoS ONE 15, e0232403. https://doi.org/10.1371/journal.pone.0232403.

Heeramaglore, M., Kolbe, T.H., 2022. Semantically Enriched Voxels as a Common Representation for Comparison and Evaluation of 3D Building Models. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. X-4/W2-2022, 89–96. https://doi.org/10.5194/isprs-annals-X-4-W2-2022-89-2022.

Kantaros, A., Ganetsos, T., Petrescu, F.I.T., 2023. Three-Dimensional Printing and 3D Scanning: Emerging Technologies Exhibiting High Potential in the Field of Cultural Heritage. Applied Sciences 13, 4777. https://doi.org/10.3390/app13084777.

Kingsland, K., 2020. Comparative analysis of digital photogrammetry software for cultural heritage. Digital Applications in Archaeology and Cultural Heritage 18, e00157. https://doi.org/10.1016/j.daach.2020.e00157.

Kirillov, A., Mintun, E., Ravi, N., Mao, H., Rolland, C., Gustafson, L., Xiao, T., Whitehead, S., Berg, A.C., Lo, W.-Y., Dollár, P., Girshick, R., 2023. Segment Anything. 2023 IEEE/CVF International Conference on Computer Vision (ICCV), pp. 3992–4003. https://doi.org/10.1109/ICCV51070.2023.00371.

König, V., 1993: Auf den Spuren deutscher Entdecker und Forscher in Russisch-Amerika. Alaska und die Nordwestküste im Spiegel alter, völkerkundlicher Sammlungen in Bremen und Niedersachsen. In: TenDenZen, II Jahrbuch Übersee-Museum, 1993, S. 27–66.

Luhmann, T., Robson, S., Kyle, S., Böhm, J., 2023. Close-Range Photogrammetry and 3D Imaging, 4th edition. ed. De Gruyter, Berlin. https://doi.org/10.1515/9783111029672.

Luhmann, T., Freist, D., Warnke, U., Albers, S., Brinkhoff, T., Fuest, S., Gollenstede, A., Herbers, M., Kaiser, R.M., Koch, S., Sester, M., Tadge, J., 2026. Digitalisierung, Visualisierung und Analyse von Sammlungsgut - Das Projekt DiViAS, in: Beiträge der 46. Wissenschaftlich-Technische Jahrestagung der DGPF. Deutschen Gesellschaft für Photogrammetrie, Fernerkundung und Geoinformation (DGPF) e.V., Hamburg, Köln.

Over, J.-S.R., Ritchie, A.C., Kranenburg, C.J., Brown, J.A., Buscombe, D., Noble, T., Sherwood, C.R., Warrick, J.A., Wernette, P.A., 2021. Processing coastal imagery with Agisoft Metashape Professional Edition, version 1.6— Structure from motion workflow documentation: U.S. Geological Survey Open-File Report 2021–1039. https://doi.org/10.3133/ofr20211039.

Patonis, P., 2024. Comparative Evaluation of the Performance of a Mobile Device Camera and a Full-Frame Mirrorless Camera in Close-Range Photogrammetry Applications. Sensors 24, 4925. https://doi.org/10.3390/s24154925.

Qi, C.R., Su, H., Mo, K., Guibas, L.J., 2016. PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation. https://doi.org/10.48550/ARXIV.1612.00593.

Ricolfe-Viala, C., Esparza, A., 2021. The Influence of Autofocus Lenses in the Camera Calibration Process. IEEE Trans. Instrum. Meas. 70, 1–15. https://doi.org/10.1109/TIM.2021.3055793.

Yang, S., Hou, M., Li, S., 2023. Three-Dimensional Point Cloud Semantic Segmentation for Cultural Heritage: A Comprehensive Review. Remote Sensing 15, 548. https://doi.org/10.3390/rs15030548.

Yang, Y., Huang, Y., Guo, Y.-C., Lu, L., Wu, X., Lam, E.Y., Cao, Y.-P., Liu, X., 2024. SAMPart3D: Segment Any Part in 3D Objects. https://doi.org/10.48550/ARXIV.2411.07184.

Zhan, K., Fritsch, D., Wagner, J.F., 2021. Integration Of Photogrammetry, Computed Tomography and Endoscopy for Gyroscope 3D Digitization. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLVI-M-1–2021, 925–931. https://doi.org/10.5194/isprs-archives-XLVI-M-1-2021-925-2021.

Zhou, Y., Gu, J., Li, X., Liu, M., Fang, Y., Su, H., 2023. PartSLIP++: Enhancing Low-Shot 3D Part Segmentation via Multi-View Instance Segmentation and Maximum Likelihood Estimation. https://doi.org/10.48550/ARXIV.2312.03015.

This contribution has been peer-reviewed.
https://doi.org/10.5194/isprs-archives-XLIX-B2-2026-779-2026