SAM-Based Detection of Structural Anomalies in 3D Models for Preserving Cultural Heritage

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Keywords: 3D Modeling, Artificial Intelligence, Cultural Heritage Protection, Drones.

Abstract: The detection of structural defects and anomalies in cultural heritage emerges as an essential component to ensure the integrity and safety of buildings, plan preservation strategies, and promote the sustainability and durability of buildings over time. In the search to enhance the effectiveness and efficiency of structural health monitoring of cultural heritage, this work aims to develop an automated method focused on detecting unwanted materials and geometric anomalies on the 3D surfaces of ancient buildings. In this study, the proposed solution combines an AI-based technique for fast-forward image labeling and a fully automatic detection of target classes in 3D point clouds. As an advantage of our method, the use of spatial and geometric features in the 3D models enables the recognition of target materials in the whole point cloud from seed, resulting from partial detection in a few images. The results demonstrate the feasibility and utility of detecting self-healing materials, unwanted vegetation, lichens, and encrusted elements in a real-world scenario.

1 INTRODUCTION

The importance of preserving architectural heritage goes beyond a simple historical and cultural obligation; it represents a fundamental responsibility towards future generations. Identifying and addressing structural flaws and anomalies in historic buildings early on is a fundamental pillar in ensuring the integrity and longevity of these monuments over time. Thus, the proposal of methodologies to efficiently assess the preservation of heritage and prevent future incidents involves a promising field of research.

These methodologies can greatly benefit from exploiting feature patterns extracted from 3D models and multi-sensory datasets. In this context, Visual Computing plays a crucial role in 3D building inspection through the development of computer vision methods that are applied to interpret, represent, classify, summarize, comprehend, and analyze content related to cultural heritage. These algorithms can be employed to automatically detect anomalies or defects in the building structure. This includes identifying cracks, deformations, or other structural issues by analyzing visual data obtained through images or scans. This aids in automated analysis and understanding of the building composition and conservation.

AI-powered computer vision algorithms can analyze images and videos of buildings to identify structural defects, damage, or irregularities automatically. Drones equipped with cameras can conduct aerial inspections of buildings, capturing high-resolution images and videos. AI can then be employed to analyze this data for structural issues. Indeed, the use of AI techniques often involves training classification models, and this training process typically relies on labeled datasets.

This work proposes an AI-driven method focused on generating annotated 3D models from a partial segmentation of a few Unmanned Aerial Vehicle (UAV) images. The proposed case studies aim to identify structural flaws on the 3D surface of old buildings. In this study, the target anomalies are self-healing materials, unwanted vegetation, lichens, and encrusted elements. All of them are detrimental to the conservation of architectural heritage and their detection aids in more effective preservation strategies and accurate inspection of the spatial arrangement of structural elements. The proposed pipeline is divided into 2 main

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Jurado-Rodríguez, D., López, A., Jiménez, J., Garrido, A., Feito, F. and Jurado, J.
SAM-Based Detection of Structural Anomalies in 3D Models for Preserving Cultural Heritage.
DOI: 10.5220/0012464000003660

In *Proceedings of the 19th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2024) - Volume 3: VISAPP*, pages 741-748
ISBN: 978-989-758-679-8; ISSN: 2184-4321

steps: (1) semi-automatic labeling of structural faults of the target building in UAV imagery using AI tools, (2) 3D point cloud image mapping, and classification using geometric and radiometric features.The main contribution of the proposed method lies in the development of a methodology for recognizing target materials in 3D point clouds in real-world scenarios and identifying harmful elements in historic buildings. This is of vital importance in architectural conservation tasks and strategies.

This document is structured as follows: section 2 presents the current state-of-the-art, reviewing relevant technologies and methodologies related to digitalization for preserving cultural heritage. Then, section 3 describes datasets to which the proposed method is targeted. section 4 outlines the proposed method, whereas the obtained results and the experiments conducted to validate our proposal are presented in section 5. Finally, the main contributions of this work are summarized in section 6, including insights toward future work that aid in further enhancing the proposed methodology.

2 PREVIOUS WORK

Built heritages face changes through time, including erosion, degradation, deformations from natural phenomena, human interventions, inappropriate restorations, etc (Li et al., 2023). More formally, the ISO 19208:2016 standard (recently withdrawn, a new standard is pending) (ISO, 2016) categorizes these defects into five major groups: mechanical, electromagnetic, thermal, chemical and biological agents. These downgrading factors contrast with the relevance of preserving built heritages and thus evidence the importance of this work.

A deep study of the preservation of built heritage using multiple technologies is provided by (Li et al., 2023). Amongst these techniques, preservation and conservation of cultural heritage are not only understood as extracting faults and defects. Instead, the digitization of cultural heritage and its dissemination has also been vastly revised (Mendoza et al., 2023), despite not being the main goal of this work. In this regard, photogrammetry, Light Detection and Ranging (LiDAR) and CAD modelling are frequent acquisition techniques. These technologies are sometimes combined with their digitization in Building Information Modelling (BIM) that enables maintaining a record of repairs and changes in cultural heritage (Moyano et al., 2020; Rocha et al., 2020). Still, the digitization is an indirect result of our work due to the reconstruction of 3D point clouds.

Regarding the detection of building anomalies, current trends involve using Convolutional Neural Networks (CNN) over imagery from UAVs and close-sensing technology. Further insight into this field is given by (Cumbajin et al., 2023). CNNs are categorized according to the target surface, kind of problem (classification, semantic segmentation, instance segmentation, etc.), network and training methodology. According to this, the detection of defects over metal surfaces is trained differently than building-based methods as they require specialized datasets. This even applies to individual defects: (Perez et al., 2019) experimented with a shallow CNN composed of convolutional and dense layers to identify moisture. For this purpose, a small collaborative dataset from copyright-free Internet images was used.

Transfer Learning has a significantly higher presence in building supervision than using custom CNNs. Amongst the most frequent CNN architectures, pre-trained VGG, YOLO, U-Net, AlexNet, GoogleLeNet, Inception and Xception networks stand out. The work of (Kumar et al., 2021) outputs the bounding box of cracks in close-sensing building images, helping to monitor them in real-time with UAVs coupled with a Jetson-TX2. Otherwise, images can be semantically segmented to highlight cracks (Mouzinho and Fukai, 2021). Region-based CNNs are also frequent in the literature by using R-CNN (Xu et al., 2021), Fast R-CNN, Faster R-CNN (Maningo et al., 2020) and YOLO (Kumar et al., 2021). The objective was to detect regions with cracks.

From the revised literature, it is clear that there are some gaps in current building monitoring. Firstly, it is mainly carried out using close-sensed imagery, rather than enabling the monitoring of large areas. Thus, surveys are far slower as they need to capture small regions of buildings. Second, CNNs are specialized in specific materials and defects. This drawback is not only caused by learning limitations but also by the lack of available datasets. This is even more visible for defects such as moisture, where RGB imagery is used instead of more suitable data sources (e.g., thermography). Unlike our work, some of the revised studies are intended for real-time tracking by communicating information with Internet of Things (IoT) communication (Kumar et al., 2021). The main drawback of the latter is that it requires planning the location of a few devices, for instance, addressing the optimal sensor placement (OSP). On the other hand, our case study provides a long-term monitoring tool for large buildings, that, however, is not a continuous tracking. Therefore, it is intended for cultural heritage whose immediate changes are of no relevance in the short term. Although this study is conducted

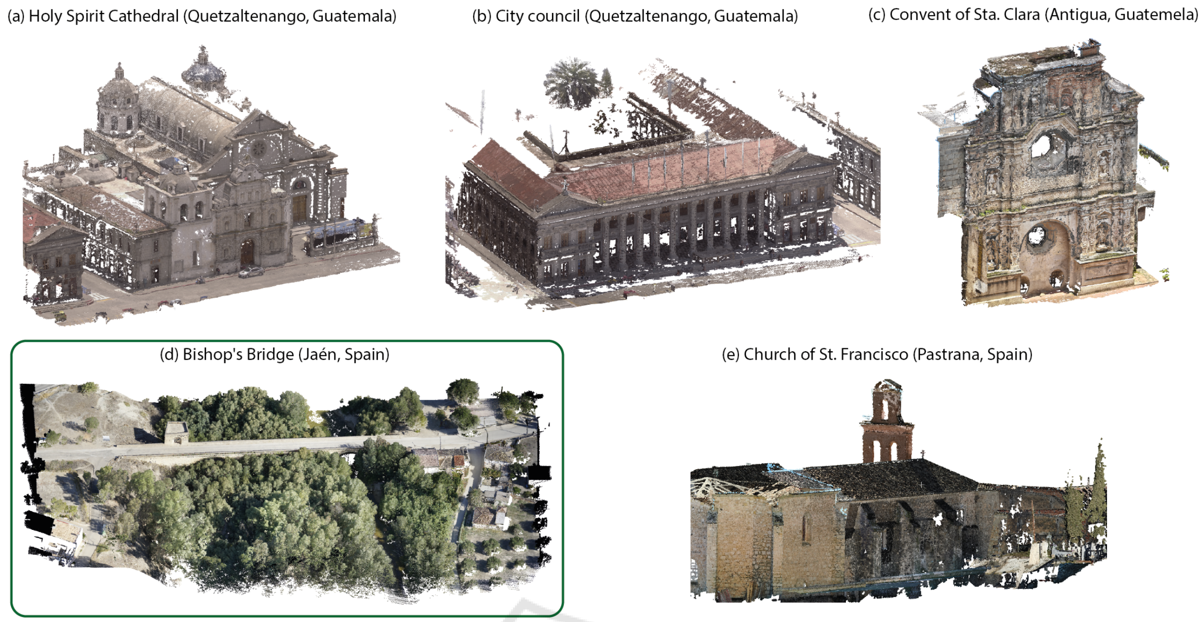

Figure 1: Selected models for the digitization of historical heritage and conservation assessment. These datasets comprise point clouds for 3D representation and high-resolution images (50 MP).

with RGB imagery, point clouds can be fed with further data sources (López et al., 2023) that can improve anomaly detection.

3 THE GENERATION OF DATASETS

The increasing use of photogrammetric techniques and LiDAR systems has facilitated the generation of a wide variety of high-detailed 3D models from many real-world scenarios. Moreover, the digitization of cultural heritage has been promoted by the proliferation of UAV sensors capable of capturing multi-view images of the whole building structure. Consequently, dense point clouds can be easily generated and they bring new opportunities to combine geometric and spatial features for multiple purposes such as object detection, semantic classification, and scene understanding.

In the field of preservation and restoration of historic buildings, the generation of 3D models allows us to achieve a more accurate assessment of current conservation status. In recent years, we have collected a huge set of 3D models of significant cultural sites and civil infrastructures. These datasets were generated by using airborne LiDAR or photogrammetry. In both cases, overlapped RGB images were captured to obtain textured point clouds. Depending on the acquisition system, the image resolution ranges from 20 to 50 megapixels (MP), whereas the point cloud densification varies from 100 to 500 points per squared meter. Figure 1 shows some results of the resulting 3D reconstructions corresponding to different places in Spain and Guatemala.

The case study of this work is the Bishop's Bridge scenario to automatically identify materials or anomalies that may pose a risk to the preservation of this structure. The Bishop's Bridge is a noteworthy example of the Andalusian Renaissance, and its construction dates back to the early 16th century. More precisely, it was built between 1505 and 1518 to facilitate passage over the Guadalquivir River. The bridge, designed on a slope to accommodate the varying levels of the supporting shores, comprises four ashlar arches. These arches are reinforced by corresponding cutwaters—curved pillars strategically placed to mitigate the force of the water and evenly distribute it across each arch. Additionally, a chapel is affixed to one of the abutments of the bridge.

4 METHODOLOGY

This section presents the workflow to detect structural anomalies in 3D architectural building models. Our method consists of two stages: the first employs a few UAV images for the semi-automated identification of anomalies in the infrastructure surface and generates segmented imagery. The second stage is

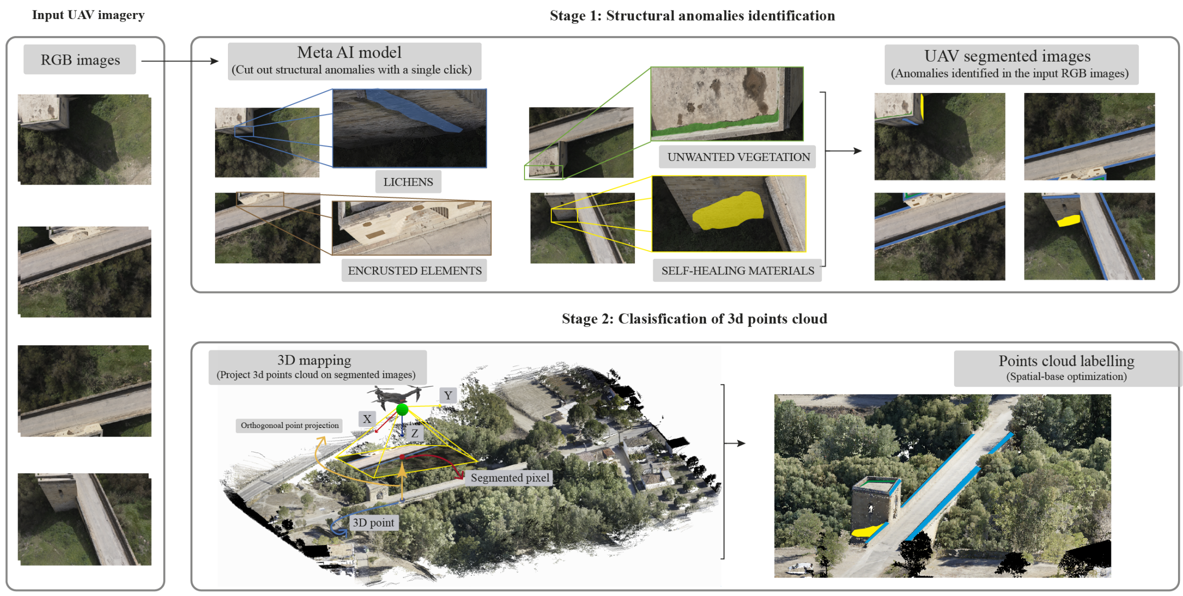

Figure 2: An overview of the proposed workflow that summarizes the main steps of the proposed solution combines an AI-based technique for fast-forward image labeling and a fully automatic detection of target classes in 3D point clouds.

the mapping of the 3D point cloud onto previously segmented images. This provides partial labeling of the point cloud. Finally, an algorithm for 3D model classification based on geometric and color features is implemented by taking the already segmented classes as a starting point, generating a fully segmented 3D point cloud.

Figure 2 provides a graphical overview of the proposed methodology. The obtained results demonstrate the reliability of our proposal in identifying anomalies such as self-healing materials, unwanted vegetation, lichens, and encrusted elements in architectural structures within real-world environments.

4.1 Structural Anomalies Identification in UAV Images

The precise classification of diverse objects within three-dimensional environments continues to pose a considerable challenge for contemporary AI models. To the best of our knowledge, a comprehensive AI model that effectively tackles the intricate task of semantic segmentation in 3D models has not been yet found. Nevertheless, amid this existing limitation, current AI models exhibit significant promise for the semantic segmentation of high-resolution images. In this context, SAM (Segment Anything Model)(Kirillov et al., 2023) must be highlighted as a valuable resource that employs advanced machine learning techniques to identify and delineate various objects in an image. Our methodology utilizes ”Segment Anything” as a semi-automatic tool to delineate specific anomalies, such as self-healing materials, unwanted vegetation, lichens, and encrusted elements, on the architectural structures of interest in images captured by UAVs.

The principle of SAM lies in its ability to conduct a meticulous analysis of the visual characteristics of images using pattern recognition and classification techniques based on geometric and textural features. This approach enables SAM to distinguish various elements within an image. However, the initial segmentation performed by SAM may not always achieve the required precision, particularly in the context of cultural heritage preservation. This is where the intervention of experts in architectural conservation and image analysis becomes essential. Following SAM's initial segmentation, these specialists review and enhance the results, applying their expertise in architecture and the historical significance of the elements under scrutiny. This review process fine-tunes and refines the segmentations to achieve precise and contextually relevant outcomes.

This intervention facilitates the correction and refinement of segmented parts, ensuring a nuanced and accurate depiction of anomalies. The hybrid nature of this approach, fusing the precision of machine learning with human expertise, substantially enhances the overall quality of the segmentation and subsequently improves the efficacy of anomaly detection. The segmentation stage generates a set of labeled images, serving as a crucial starting point for the next method phase.

Figure 3: UAV images highlighting the anomalies taken into account in this investigation.

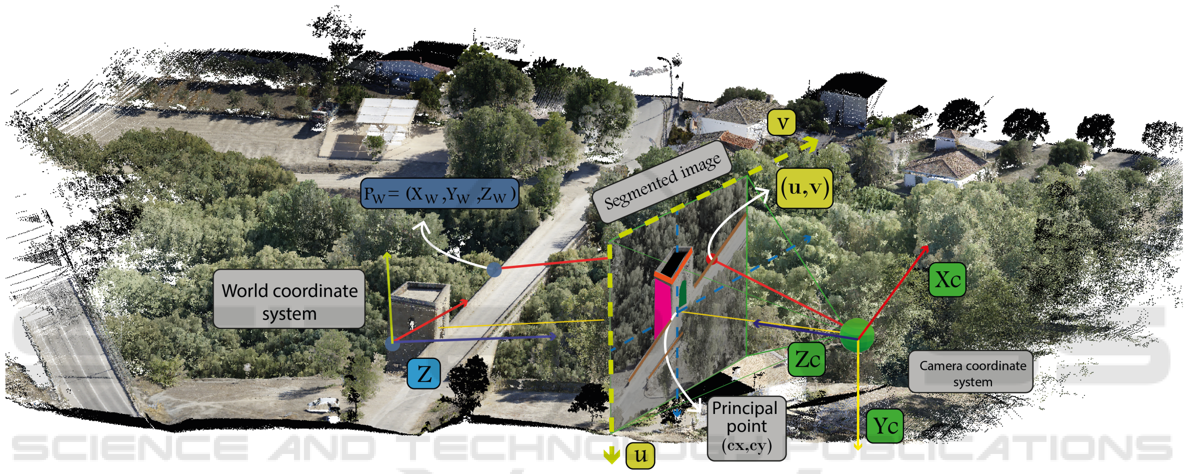

Figure 4: Graphical overview of the pinhole camera model. This describes the relationship between the coordinates $(\mathbf{X},\mathbf{Y},\mathbf{Z})$ of one point in the world space and its projection $(\mathbf{u},\mathbf{v})$ onto the image plane of an ideal pinhole camera.

4.2 Classification of 3D Points Clouds

The classification of 3D point clouds constitutes a fundamental stage in our methodology for identifying structural anomalies in 3D models. In this section, we present an algorithm to automatically 3D point cloud labelling, using the segmented UAV images generated in the previous section. This algorithm is divided into two phases: 3D mapping and point cloud labeling. The initial phase projects the 3D point cloud onto the segmented images and labels those points whose projection finds a segmented class. The second phase involves expanding these initially labeled regions in the point cloud using the following information: (1) the angle formed by the point's normal with respect to the class normal, (2) the point color, and (3) the angle of the expansion vector with respect to the perpendicular vector of the normal.

4.2.1 The 3D Mapping

The 3D mapping process estimates the projection of a single 3D point onto the image plane. This projection is computed (as depicted in Figure 4) using the pinhole camera model. Given a point $(\mathbf{P}_w)$ with coordinate $(\mathbf{X}_w,\mathbf{Y}_w,\mathbf{Z}_w)$ in the world coordinate system, the rotation and translation camera matrix ($\mathbf{R}$, and $\mathbf{t}$) which represent the camera's orientation and position in the world. The rotation matrix $\mathbf{R}$ describes how the camera is oriented, while the translation matrix $\mathbf{T}$ indicates its location relative to a reference point. Note that both matrix are derived from the extrinsic calibration process and enable to estimate the transformation from $(\mathbf{P}_w)$ to camera coordinate system $(\mathbf{X}_c,\mathbf{Y}_c,\mathbf{Z}_c)$ as follows.

$$\begin{bmatrix} X_c \\ Y_c \\ Z_c \end{bmatrix} = [\mathbf{R} \mid \mathbf{t}] \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix} \tag{1}$$

The lens distortion is modelled using radial distortion ($\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3, \mathbf{k}_4, \mathbf{k}_5, \mathbf{k}_6$), tangential distortion ($\mathbf{p}_1, \mathbf{p}_2$) and prism distortion coefficients ($\mathbf{s}_1, \mathbf{s}_2, \mathbf{s}_3, \mathbf{s}_4$). Thus, given the camera matrix ($\mathbf{K}$), composed of focal lengths ($\mathbf{f}_x, \mathbf{f}_y$) and an optical center ($\mathbf{c}_x, \mathbf{c}_y$), the coordinates value ($\mathbf{u}, \mathbf{v}$) which determine the projection of the ($\mathbf{P}_w$) to the segmented image plane is computed as:

$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} f_x x'' + c_x \\ f_y y'' + c_y \end{bmatrix} \tag{2}$$

where

$$\begin{bmatrix} x'' \\ y'' \end{bmatrix} = \begin{bmatrix} x' \frac{1+k_1 r^2+k_2 r^4+k_3 r^6}{1+k_4 r^2+k_5 r' k_6 r^6} + 2p_1 x' y' + p_2 \left(r^2 + 2x'^2\right) + s_1 r^2 + s_2 r^4 \\ y' \frac{1+k_1 r^2+k_2 r^4+k_3 r^6}{1+k_4 r^2+k_5 r^4+k_6 r^6} + p_1 \left(r^2 + 2y'^2\right) + 2p_2 x' y' + s_3 r^2 + s_4 r^4 \end{bmatrix} \tag{3}$$

with

$$r^2 = x'^2 + y'^2 \tag{4}$$

and

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} X_c / Z_c \\ Y_c / Z_c \end{bmatrix} \quad \text{if } \mathbf{Z}_c \neq 0 \tag{5}$$

Finally, it is crucial to highlight that after the 3D mapping stage, a filtering process is performed to discard occluded points. Occlusion is a common issue in three-dimensional environments and affects the accuracy of the segmentation process significantly. To tackle this, a 'z-buffer' is generated for each image during the projection stage. This buffer stores the depth of the 3D points projected from the camera position. In this way, the occluded points are identified and omitted.

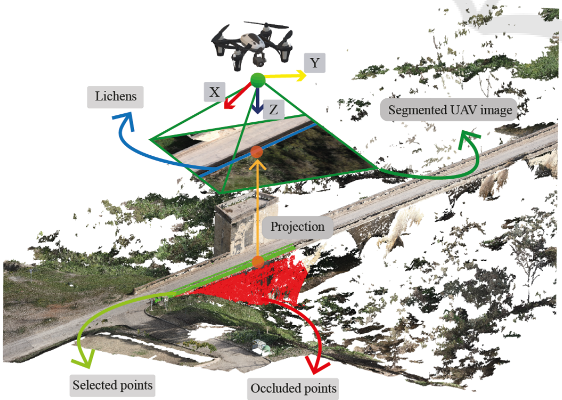

Figure 5: Visual results showing the removal of spotted occlusion (marked in red) after applying the proposed method.

In Figure 5, discarded points marked as occluded are highlighted in red. This visual representation illustrates the impact of occluded point removal, helping to improve the quality and accuracy of the final result by providing a faithful and complete representation of the segmented class.

4.2.2 Point Cloud Labelling

After performing the mapping and omitting occluded points, a partially segmented point cloud is obtained. Only the points visible in the images are labelled in this stage; for this reason, the following step is to extract a more complete segmentation of the cloud from the previously labelled 3D dataset.

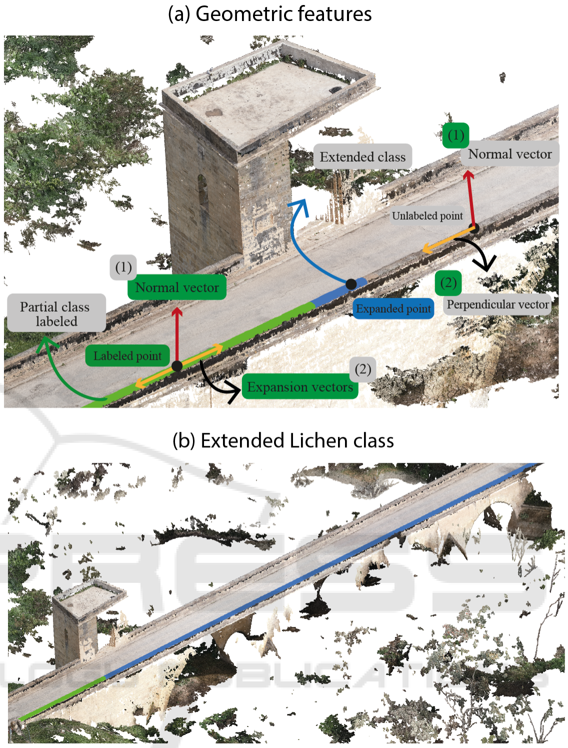

Figure 6: The proposed method to expand the initially labeled classes and generate the 3D point cloud completely labeled.

In order to address this challenge, an automatic method based on 3D geometric features has been implemented. For each labeled class, we computed: (1) a radius (r) to determine the search area in which neighboring unlabeled points will be considered (2) the expansion vector, and (3) the color gradient. In our study, after some tests, the radius is set to five times the ground sampling distance (GSD). Note that three unlabeled point features are taken into account to add the point into the segmented class: (1) the normal vector, (2) the vector perpendicular to the normal in the class plane, and (3) the color (R, G, B). If the point and class vectors are closely aligned (i.e., the enclosed angle is smaller than their respective thresholds) and the color does not diverge by more than one given threshold, the point is added to that class.

Figure 6 presents an example of how this method works to obtain the segmentation of unlabeled points belonging to the 'lichen' class. Geometric and spatial features were significantly more useful to obtain better results. In this way, those 3D points not labeled in the images can be part of the surrounding classes with which they share similar features.

5 RESULTS AND EVALUATION

In this section, we describe the results from the experiments which were carried out to validate the method in natural scenarios. The accuracy, performance, and robustness of our method were tested on several scenarios considering different architectural buildings. In summary, the resulting 3D models are characterized by a GSD of 0.7 cm, an average point cloud density of 5 thousand points per cubic meter, and a total of 8 million points. These results were obtained using a CPU (Intel® CoreTM i7-10510U 2.30 GHz) with 8 GB RAM and Ubuntu 20.04.1 as the operating system.

Section 5 shows the result of our method after performing the classification and identification of the different anomalies in the 3D point cloud. As a result, our method generates a total of 4 point clouds, one for each detected anomaly.

Figure 7: Results achieved after 3D point cloud labeling.

Regarding the performance of the method, Table 1 shows the computational cost required by the method to perform the point cloud classification in its entirety. As can be seen in the table, the cloud mapping on the images only takes 9 seconds; however, the automatic cloud labeling process requires a total of 25.4 seconds.

Table 1: Response time of the automated 3D point cloud classification.

Classification of 3D points clouds	Average (sec)
A. The 3D mapping	8.02
B. Point cloud labelling	25.4

In order to validate the results obtained, Table 2 counts the total number of labeled points after mapping the cloud on the segmented images. Then, it shows how we managed to increase the number of labeled points after applying our method, thus obtaining a completely labeled 3D point cloud.

Table 2: Comparison between 3D points labeled with a single image as reference and those labeled after applying the expansion method.

Anomalies	Single Image	Our method
Lichens	64.256	430.750
Encrusted elements	2.658	5.478
Unwanted vegetation	11.256	26.567
Healing material	26.985	75.458

6 CONCLUSIONS AND FUTURE WORKS

In summary, this study addresses the detection of structural defects and anomalies in cultural heritage.

The main contribution of our method is an algorithm to exploit the spatial and geometric features, enabling the recognition of target materials in the entire 3D point cloud. The results demonstrate the feasibility and usefulness of this approach in real scenarios, identifying self-healing materials, unwanted vegetation, lichens, and embedded elements on the 3D surfaces of historic buildings. The detection of these detrimental elements contributes to more effective conservation strategies.

The proposed method is divided into two main steps: semi-automatic labeling of structural faults in UAV images using AI tools and mapping and classification of 3D point cloud images using geometric and radiometric features.

In conclusion, this study presents a novel AI-based approach with promising results for the automated detection of structural anomalies in cultural heritage in 3D natural scenarios. The integration of

AI-based techniques and 3D point cloud analysis constitutes a valuable contribution to the conservation and preservation of architectural heritage, highlighting the feasibility and potential impact on structural health monitoring in the field of cultural heritage.

ACKNOWLEDGEMENTS

This project has been funded under the contract signed between the UNIVERSITY OF JAÉN and the companies ALBAIDA INFRAESTRUCTURAS S.A. and TALLERES Y GRUAS GONZALEZ, S.L. which regulates the work on "Multisensory Image Processing and Analysis for Material Segmentation and Characterization" (EXP. 2021 120) and the research projects with references PID2022-137938OA-I00, PID2021-126339OB-I00 and TED2021-132120B-I00.These projects are co-financed by the Junta de Andalucía, Ministerio de Ciencia e Innovación (Spain), and the European Union's ERDF funds.

REFERENCES

Cumbajin, E., Rodrigues, N., Costa, P., Miragaia, R., Frazão, L., Costa, N., Fernández-Caballero, A., Carneiro, J., Buruberri, L. H., and Pereira, A. (2023). A systematic review on deep learning with cnns applied to surface defect detection. *Journal of Imaging*, 9(10).

ISO (2016). Iso 19208:2016- framework for specifying performance in buildings.

Kirillov, A., Mintun, E., Ravi, N., Mao, H., Rolland, C., Gustafson, L., Xiao, T., Whitehead, S., Berg, A. C., Lo, W.-Y., Dollár, P., and Girshick, R. (2023). Segment anything. *arXiv:2304.02643*.

Kumar, P., Batchu, S., Swamy S., N., and Kota, S. R. (2021). Real-time concrete damage detection using deep learning for high rise structures. *IEEE Access*, 9:112312–112331.

Li, Y., Zhao, L., Chen, Y., Zhang, N., Fan, H., and Zhang, Z. (2023). 3d lidar and multi-technology collaboration for preservation of built heritage in china: A review. *International Journal of Applied Earth Observation and Geoinformation*, 116:103156.

López, A., Ogayar, C. J., Jurado, J. M., and Feito, F. R. (2023). Efficient generation of occlusion-aware multispectral and thermographic point clouds. *Computers and Electronics in Agriculture*, 207:107712.

Maningo, J. M. Z., Bandala, A. A., Bedruz, R. A. R., Dadios, E. P., Lacuna, R. J. N., Manalo, A. B. O., Perez, P. L. E., and Sia, N. P. C. (2020). Crack detection with 2d wall mapping for building safety inspection. In *2020 IEEE REGION 10 CONFERENCE (TENCON)*, pages 702–707.

Mendoza, M. A. D., De La Hoz Franco, E., and Gómez, J. E. G. (2023). Technologies for the preservation of cultural heritage: A systematic review of the literature. *Sustainability*, 15(2).

Mouzinho, F. A. L. N. and Fukai, H. (2021). Hierarchical semantic segmentation based approach for road surface damages and markings detection on paved road. In *2021 8th International Conference on Advanced Informatics: Concepts, Theory and Applications (ICAICTA)*, pages 1–5.

Moyano, J., Odriozola, C. P., Nieto-Julián, J. E., Vargas, J. M., Barrera, J. A., and León, J. (2020). Bringing BIM to archaeological heritage: Interdisciplinary method/strategy and accuracy applied to a megalithic monument of the Copper Age. *Journal of Cultural Heritage*, 45:303–314.

Perez, H., Tah, J. H. M., and Mosavi, A. (2019). Deep learning for detecting building defects using convolutional neural networks. *Sensors*, 19(16).

Rocha, Mateus, Fernández, and Ferreira (2020). A Scan-to-BIM Methodology Applied to Heritage Buildings. *Heritage*, 3(1):47–67.

Xu, Y., Li, D., Xie, Q., Wu, Q., and Wang, J. (2021). Automatic defect detection and segmentation of tunnel surface using modified mask r-cnn. *Measurement*, 178:109316.