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Developing Defect Embedded Masonry H-BIM Using Deep Learning-Based Detection and Segmentation

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Abstract

The surface of ancient masonry structures is prone to various defects over time. H-BIM assists in defect inspection digitally, which improves efficiency and saves the labor force. However, existing H-BIM of masonry structures still has limitations of low defect complexity and ideal geometric shape, and the defect information is not integrated with corresponding masonry units, lacking accurate and comprehensive prediction in structural analysis. The developed model presents detailed and realistic masonry units fused with defect information and could be used for numerical simulations. A YOLO model is used to detect and segment defects in masonry structures. K-fold cross-validation is employed during model training to mitigate the impact of category imbalance in the dataset. The YOLO model has also been employed to segment masonry units and extract their contours. The defect information is integrated with masonry units based on their positions. A case study was carried out in an ancient city wall in Suzhou, China. The generated masonry H-BIM assists the current and future protection of the structures, highlighting the feasibility of the method for the analysis of masonry structures.

Keywords: Deep learning, Convolutional Neural Network, Defect detection, Defect segmentation, Masonry structure, Heritage building information modeling, Built heritage

1. Introduction

Masonry structures are a traditional construction form of built heritages that primarily utilizes materials such as bricks, stones, and mortar. Over time, these masonry units are susceptible to various types of defects due to natural or human-induced factors, including weathering or erosion, efflorescence, missing parts, and biological colonization, among others. These defects compromise the integrity of the building and may pose risks to its structural safety. Therefore, regular inspections of masonry structures are necessary to discover and address defects early, while preemptive measures need to be taken to mitigate risks in vulnerable positions. Conventional defect detection methods often rely on manual recording and annotation, lacking automation, which can be time-consuming and labor-intensive when dealing with hundreds or thousands of masonry units (Keshmiry et al., 2024). By utilizing deep learning-based artificial intelligence algorithms, various defects can be automatically detected. Another issue is that conventional risk assessment relies heavily on human experience, which may not always provide accurate and comprehensive foresight (Stepinac & Gašparović, 2020). Digital twin technology establishes a model reflecting real-world masonry structure and integrates defect information into masonry units, enabling digital management on heritage building information modeling (H-BIM) platforms, and facilitating the management and maintenance of those positions (Tan et al., 2021). The model can also be used for further numerical simulations to analyze the failure mechanisms, assess potential risks, and provide guidance for the current and future protection of the building.

2. Literature Review

2.1 Heritage Masonry Structural Models for Simulation

The performance of masonry structures is often analyzed through numerical simulation methods. Ferretti & Bažant (2006) evaluated the stability of ancient masonry towers in terms of size effect, moisture diffusion, and chemical reaction kinetics using the finite element method (FEM). Zhang et al. (2024) conducted thermal and moisture simulations on the ancient city wall of Nanjing, studying the impact of plants on the hygrothermal conditions of the wall. Li et al. (2021) simulated the effects of plants on the microclimate and surface crystalline weathering of the city wall. Loverdos et al. (2021) proposed an image-based approach for automatically generating numerical models of cracked masonry and established a numerical model based on the discrete element method. Pereira et al. (2023) studied the mechanical properties of masonry units under loading using numerical methods.

Existing numerical simulation modeling of masonry units mostly involve ideal geometric shapes, while some scholars have indicated that more representative masonry visualizations lead to more accurate results (Erdogmus et al., 2019; Loverdos et al., 2021). In addition, some existing research only models the morphology of masonry units and mortar joints, while information associated with the health status, such as defects, is not accurately reflected at corresponding locations, which could also affect the accuracy of the analysis.

2.2 Defect Mapping in H-BIM

The defect information is often integrated into the H-BIM for future management. Some existing research has explored the mapping process, typically through the conversion of planar photo coordinates, geographic coordinates, and 3D model coordinates (Brackenbury & Dejong, 2018; Liu et al., 2021; Tan et al., 2022; Chen et al., 2023; Pantoja-Rosero et al., 2023; Yang et al., 2024). However, existing research only simply overlays the defect positions on the model surface without deeper integration of defect information with the building components. For masonry structure models (Masonry-BIM), a more comprehensive approach could involve generating the arrangement of each masonry unit on the model and then assigning defect information to the corresponding masonry units according to the positions. This allows knowing the defect types present in each masonry unit on the H-BIM to precisely assess the risk of each unit. Furthermore, masonry units could be more precise than the entire wall surface in allocating defect attributes to them, enhancing the reliability of structural numerical simulation analysis.

2.3 Deep Learning-based Defect Detection and Segmentation

Deep learning has been employed for defect detection and segmentation of buildings to enhance inspection efficiency and accuracy. Some research utilizes computer vision techniques to detect objects in images. Huang et al. (2024) fused visible images with thermal images, developed a dataset of cracks in masonry structures, and evaluated the improvement in crack segmentation accuracy through six convolutional neural network (CNN)-based models. Wang et al. (2019, 2020) used a Faster R-CNN model based on ResNet to detect weathering and spalling in historic masonry structures and later utilized Mask-CNN to segment damage on yellow-glazed tiles. You Only Look Once (YOLO) is another model which has many applications in object detection and instance segmentation because it is adaptable to targets of various sizes and shapes with good detection speed and accuracy (Casas et al., 2024). Yan et al. (2024) employed the YOLO model to detect dislodged thin bricks on the roof pedestals of classical gardens. Li et al. (2023) used a YOLO model to identify cracks, chalking, plant damage, and ubiquinol on the surface of the Great Wall. Apart from image-based methods, there are also research based on point clouds. Valero et al. (2019) used a logistic regression classification algorithm to detect cracks, material loss, and discoloration on the facades of castles and churches.

A limitation of existing research is that the detected categories are often singular or limited, or the complexity of the surfaces is low, such as walls with uniform background colors or sparse defects. This limitation hinders deep learning models from achieving high accuracy when encountering dense defects or irregularly arranged cluttered masonry units.

2.4 Deep Learning-based Masonry Unit Segmentation

For the segmentation of masonry units, image-based or point cloud-based methods can be used. Image-based methods are relatively straightforward for regular-shaped masonry units. When masonry structures have random rubble and joints with irregular shapes and sizes, such as in ancient architectures, it will incur more training costs that need to classify and label each category of masonry unit with different sizes and materials multiple times (Wang et al., 2020). Valero et al. (2020) and Forster et al. (2023) employed a CloudCompare plugin based on the 2D Continuous Wavelet Transform (CWT) to segment masonry units and extract their contours from laser point clouds. This point cloud-based method is more suitable for irregular rather than flat wall facades (Güneş et al., 2024).

The objective of the present paper is to enhance the information integrity of masonry H-BIM, and investigate a solution of generating a lightweight masonry model that includes detailed and realistic masonry units mapped with defect information, enabling precise localization and assessment of potential risks to assist management personnel in protecting the building currently and in the future.

3. The Proposed Method

To achieve the objective, the following methodology has been proposed, as shown in Figure 1. The procedure of the methodology includes data acquisition, masonry defect detection and segmentation, masonry unit segmentation, and integration of defect information with masonry H-BIM.

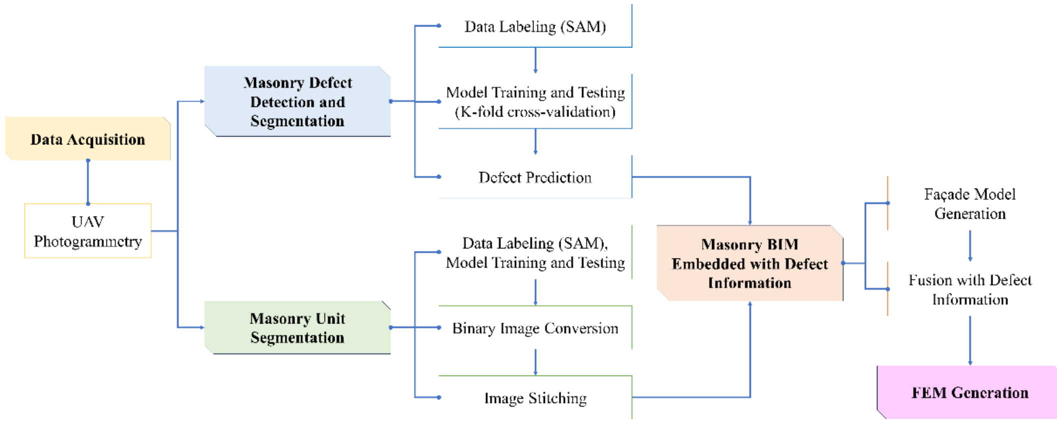

Figure 1: Proposed methodology

3.1 Masonry Defect Detection and Segmentation

A YOLO model is developed and trained to detect and segment defects on masonry structures because of its good detection speed and accuracy on large-scale masonry structures. The process involves data acquisition, data labeling, model training, and model testing. Data acquisition involves capturing front views of the masonry facades using unmanned aerial vehicle (UAV) photogrammetry, followed by proportionally dividing the images into training, validation, and test sets. Images are cropped to a uniform pixel size to improve training effectiveness. During data labeling, four categories of defects in masonry structures are identified: erosion (further divided into deep erosion and superficial erosion based on the extent of damage), efflorescence, missing parts, and biological colonization. The Segment Anything (SAM) tool (Kirillov et al., 2023) is used for labeling to generate masks for the corresponding objects in the training images. Subsequently, the model is trained and tested for detection and segmentation. To mitigate the impact of category imbalance in the dataset, K-fold cross-validation is employed during training. This method involves dividing the original dataset into K subsets, iteratively using one subset as the validation set while the remaining K-1 subsets are used for training the model. The model is trained and validated multiple times, and the average of the results is used as the best weight. After multiple adjustments and optimizations of parameters such as initial learning rate, epochs, batch size, etc., the model file with the best weight is obtained for defect detection on the target masonry structures.

3.2 Masonry Unit Segmentation

Another YOLO model is developed for the segmentation of masonry units. Data labeling, model training, and model testing are also performed. In data labeling, the labeled objects became each masonry unit, which is the brick and stone block. Masks are added on the blocks in SAM. The model with the optimal weight after training is used for prediction. The images used in the prediction dataset in this step is the same as the prediction dataset used in 3.1, in order to maintain a consistent coordinate system in subsequent processing. The predicted images are converted with a black background and the masks are set to white to derive the binary images of the masonry structure, which clearly distinguishing between blocks and joints (white for blocks, black for joints), as shown in Figure 2. The binary images are then spliced to form an entire side of the wall.

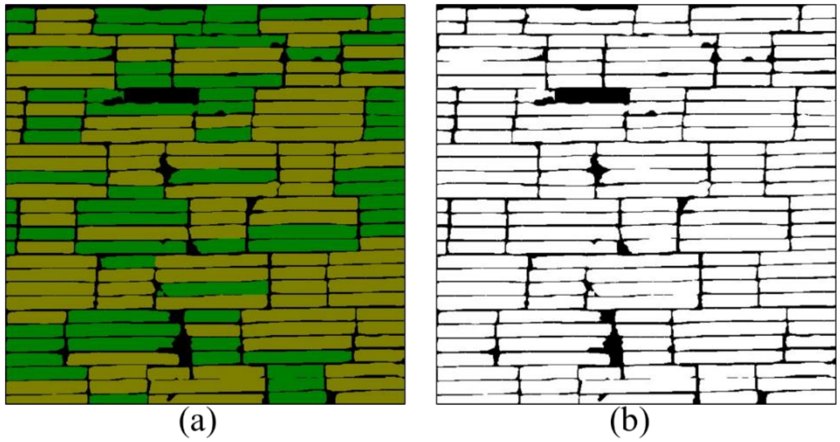

Figure 2: (a)The segmentation result of masonry units (different color represent different materials); (b) The concerted binary images of the masonry arrangement

3.3 Masonry H-BIM Generation and Defect Fusion

Images of the structure are aligned according to their position and the image point cloud is generated after alignment. The facades are segmented from the image point cloud and then using the "point to mesh" method, these parts are fitted into plane surfaces to generate lightweight facade models. Then, the binary images obtained in 3.2 are used for the arrangement of the masonry units on the facade models. Based on the black-and-white values, the blocks and joints can be automatically divided by parametric language and then projected onto the surface of the facade model.

After the generation of the façade model, the defect information is fused with the masonry units based on their positions. The coordinate system is set as shown in Figure 3. The coordinates of the defect masks in each predicted image are transformed into global coordinates, and masonry units at corresponding positions are assigned typical defect attributes. The final obtained model accurately reflects the shape and size of masonry units, also integrate relevant defect information at the corresponding locations.

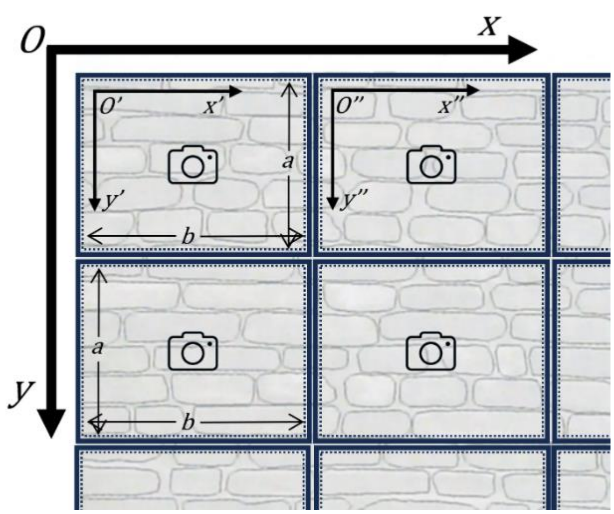

Figure 3: Set of the coordinate system

3.4 FEM Generation from the H-BIM

The obtained defect-integrated masonry model is then imported into FEM software for analysis. Material properties of bricks and joints are defined, and contact coefficients between elements such as friction coefficients are set. Different value of coefficients is assigned to each element based on the position of defect, such as Young's modulus, thermal and moisture conductivity coefficients, etc. Finally, the simulation is conducted under typical external environmental conditions.

4. Preliminary Results

The results involve a case study of an ancient city wall in Suzhou, China. The construction materials of the structure include bricks, stones, earth, mortar, and a small amount of wood. The stones are diverse in type, shape, and size. The ancient wall exhibits various defect categories such as erosion, efflorescence, missing parts, and biological colonization, with a high quantity and density. The complexity of this ancient wall poses significant research challenges, highlighting the feasibility of the methods proposed in this article for the analysis of masonry structures.

4.1 Data Preparation

The ancient walls were captured through UAV photogrammetry, as shown in Figure 4. The obtained images were used for YOLO model training and defect prediction. To prepare the YOLO dataset, images of three sides of the walls were used for model training and testing, while the last part of the wall was used for defect prediction and generating the H-BIM model of the masonry structure. During image acquisition, the camera needs to be kept as parallel to the wall as possible. For the images used for prediction, each image was removed distortion, and then all images were stitched to form a complete picture of the entire ancient wall surface. In the stitched complete picture, parts that do not belong to the wall, such as the ground and sky, were removed, as shown in Figure 5. This step was taken to facilitate the set of the wall coordinate system and match it with the point cloud coordinate system.

Figure 4: UAV photogrammetry at the ancient walls

Figure 5: Regions to be removed and to be corrected distortion in the stitched picture.

4.2 Masonry Defect Detection and Segmentation

500 uniformly cropped images were used for training. Five defect categories were defined for mask labeling, including *Deep erosion*, *Superficial erosion*, *Efflorescence*, *Missing part*, and *Biological colonization*. In the data training process, YOLOv11m-seg was selected as the pre-trained model, which offered moderate performance with acceptable accuracy without wasting resources. The dataset was divided into five subsets for K-fold cross-validation to mitigate the impact of sample category imbalance. The obtained training weight file best.pt was used for defect detection and segmentation on the other part of the ancient wall. Some prediction results are shown in Figure 6. In the images, red masks with the label "bio" stands for "*Biological colonization*", light blue masks with label the "deep" stands for "*Deep erosion*", white masks with the label "superficial" stands for "*Superficial erosion*", green masks with the label "salt" stands for "*Efflorescence*", and dark blue masks with the label "hole" stands for "*Missing part*". It can be observed that the trained model accurately detected and segmented the majority of defects. There were a few inaccurate detections that need further improvement. For example, some small plant leaves were not detected, some large areas of biological colonization or efflorescence could not be completely segmented, some bricks without defects were misidentified as erosion, and there were cases of repeated boxing in some locations.

Figure 6: Defect detection and segmentation results

4.3 Masonry Unit Segmentation and H-BIM Generation

The contours of the masonry units in the ancient wall were detected using the trained YOLO model and converted into binary images, as shown in Figure 7(a). The wall surface was extracted and the binary image was projected onto the wall surface, then blocks and joints were automatically generated through parametric language, as shown in Figure 7(b). Subsequently, the defect information was assigned to the masonry units. Since image distortion had been corrected and non-wall parts had been removed in the previous step, the coordinate systems of the ancient wall surface in the images and the modeled wall surface from the point cloud were consistent. This allowed for the direct location of defect information to the corresponding masonry units on the model, as shown in Figure 7(c).

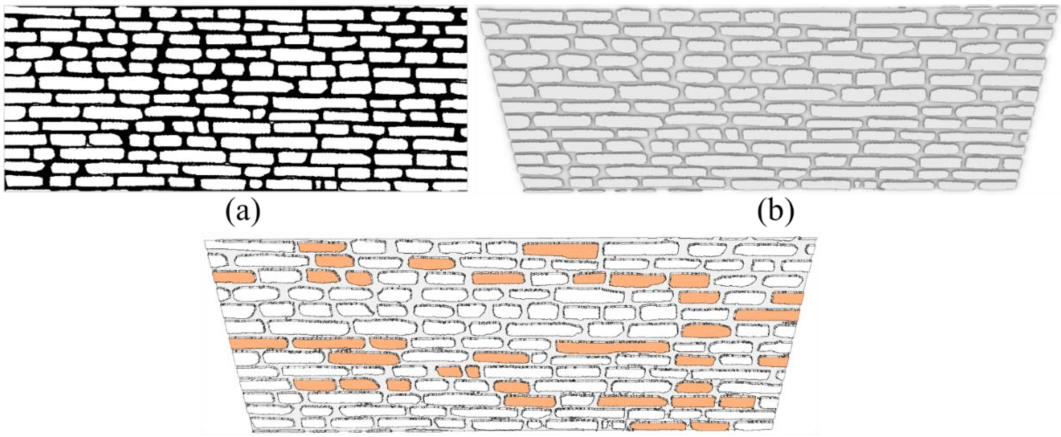

Figure 7: (a) Binary image of the entire wall; (b) Facade model; (d) Facade model with efflorescence information.

5. Discussion

The results involve a case study of an ancient city wall in Suzhou, China. The proposed model presents detailed and realistic masonry units, fused with defect information. The YOLOv11 model is used to detect and segment defects on masonry structures. K-fold cross-validation is employed during model training to mitigate the impact of category imbalance in the dataset. The defect information is fused with the masonry units based on their positions. In future work, the masonry H-BIM model integrated with defect information will be imported into numerical simulation software for analysis. To ensure the reliability of the analysis, subsequent tasks will include investigating the properties of the filled earth inside the ancient wall, determining the loads on the wall and recording the surrounding environment, etc., in order to establish a comprehensive numerical simulation model. The complexity of this ancient city wall poses great research challenges, demonstrating the feasibility of the proposed method for masonry structure analysis.

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