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Real-World Applications of Artificial Intelligence in Architecture

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Abstract. Real-world applications of Artificial Intelligence (AI) in architecture have been explored more recently at Technical University (TU) Delft by integrating AI in Design-to-Robotic-Production-Assembly and -Operation (D2RPA&O) methods. These embed robotics into building processes and buildings by linking computational design with robotic construction and/ or operation of building components and buildings. This paper presents two case studies in which AI-supported D2RA is implemented in a multidisciplinary approach that requires the integration of research domains such as architecture, robotics, computer and material science.

Keywords: Architectural design · Robotic construction · Computer vision · Human-robot interaction · Deep learning

1 Introduction

Design-to-Robotic-Production-Assembly and -Operation (D2RPA&O) methods [1] integrate robotic approaches in building processes and buildings. They consist of computational and robotic methods that address the whole process from computational design to robotic building construction (D2RP&A) and operation (D2RO). They have been advanced in the case studies presented in this paper with focus on Artificial Intelligence (AI) supported assembly strategies aiming at simplifying the perceptual and semi-/ automation tasks.

1.1 State-of-the-Art

Robotically supported approaches have been successfully introduced in the manufacturing industry since the 70s. In the last decade, researchers and practitioners explored their potential in architecture and building construction [2–4] and meanwhile AI-supported approaches are increasingly being considered. For instance, assembly approaches explored at U Stuttgart and ETH Zurich in projects such as Hive[1] and Hanging

[1] Link to the Hive project from U Stuttgart: https://www.icd.uni-stuttgart.de/projects/hive-a-human-and-robot-collaborative-building-process/.

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Gardens[2], respectively, involving humans working alongside the robots [2, 3] advance human-assisted robotic processes. Nevertheless, collaboration between human and non-human agents requires human and non-human agents to work not only side-by-side but together.

1.2 Contribution

The AI-supported D2RA approaches presented in this paper involve collaborative assembly at building and componential scale relying on Computer Vision (CV) and Human-Robot Interaction (HRI), respectively. Both facilitate the construction of larger structures from smaller components, while the robot system (a) collaborates with the human, (b) monitors and reacts to the human in real-time, and (c) is able to learn from the human during the construction process. These approaches have been tested in two case studies involving experts from architecture, robotics, and computer science. They are presented in the implementation section, whereas results are discussed in the concluding section.

2 Implementation

The case studies presented here involved the development of outdoor and indoor furniture that is requiring assembly at building and componential scale, respectively. They have been implemented with MSc students at TU Delft, who developed virtual and physical prototypes in order to test proposed designs (Figs. 1, 2, 3, 4 and 5). The students worked in groups and were tutored by experts from architecture, robotics, and computer science.

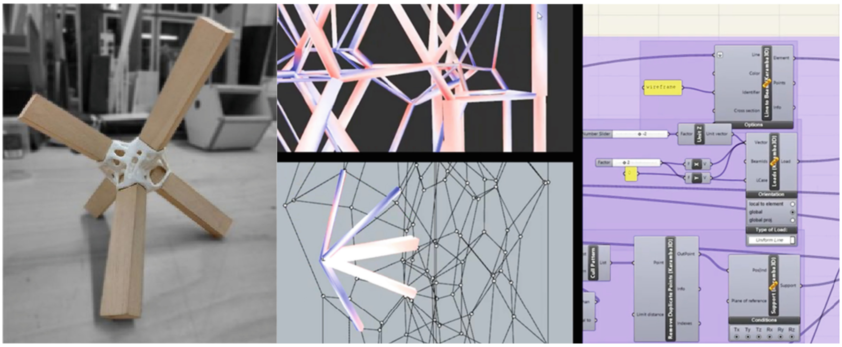

Fig. 1. Larger structurally optimized structure (right) assembled from linear elements of various sizes connected with 3D printed nodes (left).

[2] Link to the Hanging Gardens project from ETH Zurich: https://ethz.ch/en/news-and-events/eth-news/news/2021/11/robots-build-new-hanging-gardens.html.

2.1 D2RA at Component Scale

Assembly at componential scale is required in architecture because of the large scale of buildings that are then constructed from smaller-scale components assembled into larger wholes. The robot relies on CV to implement tasks, such as moving subcomponents i.e., linear elements near the assembly point, while the human helps placing the elements into the node. CV involves detection (of position, size, and orientation) without using markers which streamlines the process and takes advantage of today's AI-supported technologies [5].

2.1.1 Architectural Design

The to-be-assembled furniture components were designed with the notion of "hybrid componentiality" in mind. The subcomponents consisting of structurally optimized 3D-printed nodes and wooden linear elements that are assembled into a larger structure rely on Grasshopper scripts that are ensuring variable Voronoi-cells distribution at the material scale and structural optimization at the component scale. This implies that size and density of cells address functional i.e., architectural requirements, while variation in length and size of the linear elements comply with structural requirements (Fig. 1).

2.1.2 Computer Vision

CV has been used to identify specific locations from which the subcomponents i.e., linear elements of various sizes and 3D-printed node, are grabbed by the robotic arm using only camera(s) and no individual markers. Digital cameras are placed in a top view position, and various image processing methods are implemented in order to (a) identify the node and the linear elements, (b) estimate their individual sizes and their respective center points (Fig. 2).

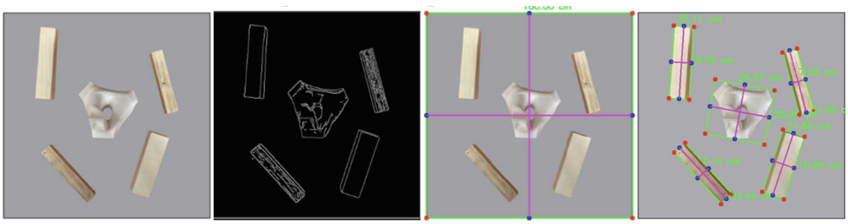

Fig. 2. CV is employed to detect the location and center points of subcomponents.

Subcomponents are detected (as a set of elements) and the set of associated bounding boxes by means of contour-finding techniques. These are compared to a query identifying the element with the bounding box that is the closest to be picked up, while coordinates of center points are computed and sent to the robotic arm[3].

[3] These steps were implemented in Python using the OpenCV library for image processing. The open-access Github repository including two Google Collaboratory guiding notebooks and a Python library show how the pipeline has been implemented.

2.1.3 Human-Robot Interaction

In the actual assembly phase, the CV algorithm links to the robotic process in order to allow the robot to identify the specific work frame and its components. While identifying and grabbing the linear components is automated, their assembly into the node is HRI-supported (Fig. 3). This implies that the robot is bearing most of the load of linear components during assembly, while the human positions them into the node hence, ensuring successful completion of the assembly task.

All robot poses and planned trajectories during the pick-and-place task are regulated via a Cartesian impedance controller [6]. This controller ensures safe human-robot collaboration via the relatively low stiffness that the robot maintains while in operation, in order to respond to potential physical collisions in a human-friendly manner [7, 8].

Fig. 3. Automated and HRI-supported assembly sequence relying on CV to pick-and-place linear subcomponents into the designated node.

After completing an extrinsic calibration to provide the robot with the necessary reference frames for the table where the subcomponents are and the final node position where the assembly is to take place, CV-supported robotic assembly is implemented. While each subcomponent's position is identified with help of CV, the robot plans a trajectory from identified position to the node position. As soon as the node position is reached the robot reduces the stiffness in order to allow the human to place the subcomponent into the node by means of physical interaction.

In the presented system, AI has been used for implementing robotic operations as demonstrated by the human. Future steps are aimed at training the system to detect other/unknown objects and identify faulty parts. Also, by employing reinforcement learning [9] the goal is in the next step to optimize trajectories and sequence of assembly beyond the one implemented in this case study.

2.2 D2RA at Building Scale

Similar to the assembly at component scale, assembly at building scale aims to create larger wholes from smaller parts. In the presented case study, in addition to assembly, disassembly and reassembly were introduced in order to achieve spatial reconfiguration in the TU Delft library. Such reconfiguration is required when seating areas for workshops (involving collaborative work sessions), events (requiring a stage and seating for the audience), exhibits as well as lounging and studying activities take place simultaneously or in short sequence.

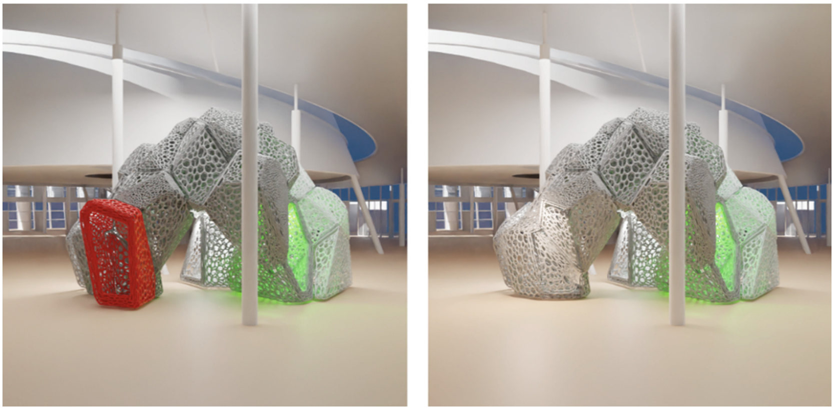

Fig. 4. Red movable component (left) and available component lighted green (left and right).

Reconfiguration is implemented in this case using a Voronoi-based design at material and component scales with varying degrees of porosity (Fig. 4), aiming at addressing both passive and active behaviors such as structural strength, physical comfort, and reconfiguration requirements, respectively. The Voronoi-based design facilitates spatial reconfiguration by attachment, detachment, and reattachment of larger components i.e., boots to create various functional configurations. The challenge for users to identify availability of the boots and reconfiguration modes ranging from dispersed to clustered configurations has been addressed by means of CV and AI-supported object recognition (Figs. 4 and 5). Furthermore, the challenge for users to move components from one location to another has been addressed by implementing a highly porous, lightweight material design. Together they facilitate the required spatial reconfiguration.

2.2.1 Architectural Design

Spatial reconfiguration has various challenges in terms of function, form, and requirements for lightweight. These were addressed with the Voronoi-based component and material design that involved consideration with respect to stability, lightweight, and comfort requiring variable stiffness [10]. The stiffness is tuned by mapping varying cell sizes according to structural analysis and required stiffness. The smaller the cells, the denser and stiffer are the structure.

For the proof of concept, manual instead of automated spatial reconfiguration was chosen as in principle both require an AI-supported approach to implement reconfiguration, which was the focus of this case study.

2.2.2 Computer Vision and Artificial Intelligence

Spatial reconfiguration relied on CV and AI for identifying (a) detached Voronoi-based components i.e., booths and (b) the places where they are supposed to be reattached (Fig. 5). The Deep Learning (DL) model was trained from scratch on a handcrafted (in this case synthetic) dataset to perform the task of visual placement. The input and output of the model are images, pointing to the input at a specific stand-alone component i.e., booth, and the output indicating the position and orientation in the constellation [3].

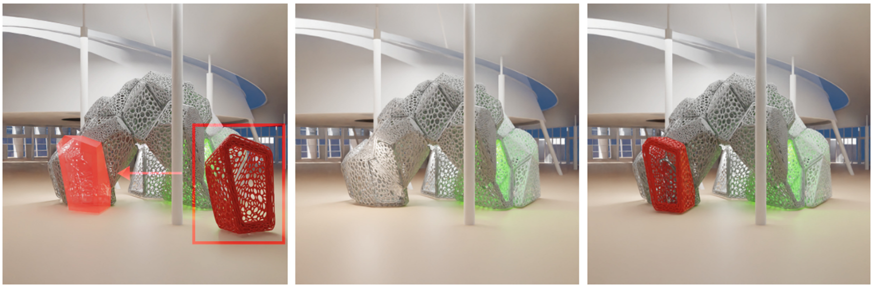

Fig. 5. Object and placement recognition for the ‘missing’ component (left), input image with the missing part (middle) and the ‘ground truth image’ (right).

In the presented problem, all Voronoi-based components were part of the constellation with their own individual base configuration and were labelled with numbers indicating the correct placement within the constellation. The challenge was to predict the correct placement i.e., the object’s number given an input image of the component taken by the user. In order to achieve this, a synthetic training and validation dataset has been created to develop a DL model for Object Detection (OD). Due to the specific configuration, no pre-trained model was available for effective deployment; hence, the students trained an OD model from scratch. For the training set, the Voronoi-based components were randomly distributed in a 3D model of the library and around 3000 images were generated from the scattered objects from various viewpoints. 80% of the data was used for training and 20% for evaluation. The synthetic dataset was then curated by simulating a realistic scenario where the images were taken from real objects in the library.

The Yolo[4] model [11] was trained on the created dataset to predict the objects’ id numbers of the components with acceptable accuracy and confidence. The online available demo[5] shows randomly placed components that are detected in real-time using the trained OD model with the probability of specific components being present within the bounding box shown in the text box (Fig. 6, right). These probabilities are used to classify an object as a true positive (correctly detected) or false positive (wrongly detected) and set a confidence level as a parameter for measuring the precision score for the object detection model. In this case, a confidence level of 0.95 from 1.00 has been achieved.

With this AI-supported approach spatial reconfiguration based on assembly, disassembly, and reassembly principles is easily implemented as long as the components are lightweight, and users identify them easily, as presented in this case study. Alternatively, a robotized reconfiguration can be considered.

[4] Yolo uses neural networks to provide real-time object detection.
[5] Link to RB-page: http://www.roboticbuilding.eu/project/human-robot-interaction-for-d2ra/.

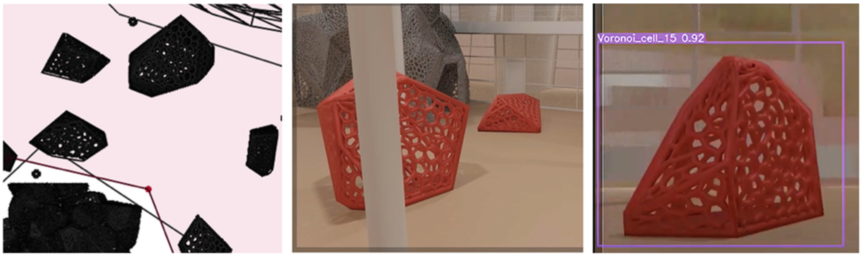

Fig. 6. Random camera and components distribution within the 3D model of library top view (left), input image from the setting (middle), and object recognition with 0.92 confidence level (right).

3 Conclusion

The presented AI-supported assembly approaches at componential and building scales are proof of concept for a range of real-world applications in architecture. They aim to support semi-/ automated tasks. At componential scale, the assembly process is not fully automated using real-time visual feedback and precise position control, instead the process is semi-automated with the human collaborating with the robot when implementing more complex tasks. Similarly, at building scale disassembly and reassembly are implemented as collaboration between human and non-human agents.

Solving a 3D puzzle as employed at building scale is a relatively unexplored field in CV. The trained models are arguably overfitted on the environment they are trained on, and will not work in a different environment. They could be used as pre-trained models but should be finetuned when used in a different environment or with different style objects. Also, the amount of training samples is limited; hence the performance is not very accurate. There is still a gap between the reasonable results achieved in the presented case studies and their employability in real life.

When it comes to CV at componential scale, proper data augmentations can really help improve on performance and robustness of any model, if the data augmentation strategy is carefully designed. In the presented cases a general set of data augmentations involving crops and slight rotations have been used. Furthermore, the use of impedance control offers many benefits during HRI, however, it also limits the accuracy of the robot end-effector positioning as well as the speed/ response time of the robot. These limitations are relatively insignificant when compared to the many benefits of allowing humans to work and collaborate safely within the robot's workspace. A more accurate and faster positioning controller would instead require high gains which could result in large accelerations/forces making collaboration with the humans unsafe.

While employed approaches are not new, their integration with D2RA methods advances current state-of-the-art explorations in AI mainly through the integrative multidisciplinary approach for real-world applications in architecture. The challenge for the future is to identify which architecture-related tasks will be fully- or semi-automated and how AI can support those. Furthermore, scaling up towards industrial applications using presented approaches presents challenges. For the HRI-supported assembly, the challenge is the payload limitation of existing collaborative robots, which are unable to handle heavier components. For the CV-specific aspects more robust object detection is needed considering that construction sites are 'noisy', due to various equipment, materials, and people. An option to circumvent the need for a very complex CV pipeline is to train instead data-driven object detection models, which will be addressed in the future work.

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