Layer-by-layer Pick and Place Collaboration between Human and Robot using Optimization

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Robotic pick-and-place (P&P) has been widely utilized in manufacturing and architectural construction since the 1980s. However, the lack of inherent sensing capabilities in robots has limited their ability to adapt and respond to changes in design or environment. To address some of these shortcomings, this paper proposes an interactive robotic brick-laying workflow using a vision-based sensing framework to inform and optimize brick placements in consecutive layers. The proposed implementation is comprised of three major computational frameworks: (1) digitally reconstructing and analyzing the current state of the assembly, (2) optimizing placement targets based on the digital representation of the environment and desired multi-objective optimization goals, and (3) planning robot motion for the next layer of brick-laying. Within this workflow, the vision-based feedback pipeline simultaneously reconstructs and localizes the already-built assembly. This geometric information constitutes the basis for the multi-objective optimization stage. The placement targets are adaptively calculated to build the next layer upon the existing assembly while optimizing for structural stability, accounting for unforeseen deviations between layers, and allowing for human intervention and modification throughout the process. By proposing an interactive robotic brick-laying workflow, the paper explores the prospects for leveraging the capabilities of robotic pick-and-place technology and integrating it with vision-based sensing frameworks to achieve optimal results in construction. Furthermore, by examining the effectiveness of a multi-objective optimization method as an adaptive design driver, this paper contributes to the development of novel computational strategies that can enhance the flexibility and adaptability of robotic construction systems.

Keywords: *Pick-and-place, Human-robot Interaction, Robotic Fabrication, Multi-Objective Optimization*

INTRODUCTION

Integration of robotic solutions has been a topic of interest in architecture and construction since the early vision of construction robots. Within this context Robotic pick-and-place (P&P) tasks has been extensively studied in manufacturing and construction for decades. However, as pointed out by Bechthold, (2010), highly customized, dynamic, and complex nature of construction and design workflows poses significant challenges for conventional robotic solutions due to the lack of sensing capabilities required to respond to changes in the environment or design. This limitation inherently impacts the application feasibility of robotic solutions in complex environments and scenarios. Recent advancements in computational hardware and sensor technology, however, have enabled the integration and handling of sensor data more feasibly, opening up new possibilities for construction robots.

To address some of the challenges present at construction environments, researchers previously suggested improvisational methods, in which the machine agent follows a continuous cycle of receiving sensory input, decision making, and take an action on the environment until the desired task is complete (Mueller et al., 2019; Peng et al., 2018). This allows the robotic system to continuously adapt to changes in the environment, often using a discretized representation of the world. Similarly, Rajan & Saffiotti (2017) suggest that such approaches require the robotic system to have a comprehensive understanding of their environment, the ability to reason over possible actions, and execution to achieve desired objectives.

To explore the potentials of such improvisational approaches in simple assembly tasks, we explored Multi-Objective Optimization (MOO) technique as a basis for motion planning. In this paper, we present a 'self-correcting' methodology for discrete block structures that leverages the unique characteristics of such construction units like bricks. Our approach involves a feedback loop that informs the generation of robot targets in a turn-taking process during robotic operations, enabling human involvement in design and fabrication procedures, aiming to establish a cyber-physical workflow, Menges (2015). The method involves the optimized layer-by-layer placement of bricks using turn-taking interaction between human and robot to create a wall/arch structure. With this approach, we aim to demonstrate how human input can be effectively integrated into optimized robotic processes to achieve improved design performance and more efficient construction practices.

BACKGROUND

Our investigation into interactive and adaptive robotic assembly tasks using vision-based feedback loops draws from a wide range of interdisciplinary collaborations across computational design, robotics, computer science, and architectural engineering fields. Within this paradigm, this study was built upon preceding work in human-machine collaboration, interactive and adaptive fabrication literature and is a culmination of theories and approaches presented in this section.

Human-Machine Interaction

The "perceive-reason-act" model describes distinct processes in which an agent (e.g., a robot or computer program) receives sensory input, takes action, and repeats the cycle, or perceive the environment, uses reasoning or decision-making processes, and then takes action, Marr (2010). These models are used in cognitive psychology and artificial intelligence to understand how humans and machines make decisions based on information processing and cognitive processes. The concept of "perceive-reason-act" was established since the 1980s and 1990s, Whitehead & Ballard (1991), and it is important to acknowledge its historical context to clarify robotic solutions. Similarly, Umbrico et al., (2020) have done research has been focused on incorporating advanced cognitive features, such as perception, event and activity recognition, and dynamic adaptation, to improve control systems in construction robots.

Within this context, researchers have been exploring different feedback loops to facilitate human-robot interaction in various stages of manipulation tasks environment. Willis et al., (2010) coined the term “interactive fabrication”, and proposed more intuitive and interactive interfaces instead of complex digital fabrication pipelines by creating purpose-built tools that allows users to directly interact with the fabrication system. Since the early conceptualization of interaction in fabrication scenarios, there has been growing interest in exploring novel interaction modalities and interfaces to enable information flow from the user to the fabrication system.

In this body of literature, Pinochet (2016) proposed a new model of human-machine interaction that promotes creativity and cognition in the design and making process by using body gestures and imbuing fabrication machines with behavior. Similarly, Bard et al. (2016) showcased two projects that utilized live motion capture, visualization, and custom robotic tooling to extend historical construction techniques through hybrid digital/physical workflows in the building trades. Building on this concept, Mitterberger et al. (2022) demonstrated Interactive Robotic Plastering (IRoP), a system that enables designers and skilled workers to create complex in-situ plasterwork using an interactive computational model and audio-visual guidance. Lastly, Mueller et al., (2019) presented a formative fabrication workflow in which motion planning was entirely informed by the user for the tooling operation carried out by the machine agent.

Feedback Loops in Fabrication and Assembly

Architectural robotic fabrication traditionally relied on linear CAD-CAM processes, but recent advances in computer vision and open-source electronics have enabled adaptive fabrication; this approach utilizes material feedback for robotic response, and there are two main approaches to achieving this. The first approach involves deploying design rules based on real-time feedback of varying materials' properties, while the second approach involves recording and analyzing human actions to inform robot control schemes. Shaked et al. (2021) suggest that the integration of these approaches will enable robotic arms to react to varying material scenarios in an adaptive fabrication process. Ercan Jenny et al. (2022) explore a new spray-based 3D printing technique called Robotic Plaster Spraying (RPS) which utilizes cementitious plaster. They combine RPS with an augmented interactive design system, Interactive Robotics Plastering (IRoP), to allow users to design directly on the construction site.

Capunaman et al. (2022) propose a vision-based sensing framework that enables robotic tooling operations on indefinite surfaces. Their study presents a low-cost, open-source foundation for future research into complex design-fabrication scenarios. In a similar vein, Brugnaro et al. (2016) present behavioral construction as another adaptive robotic fabrication framework that relies on an agent-based system, a custom weaving end-effector, and coordinated sensing strategy.

Han & Parascho (2023) propose an improvisational method for construction, where humans lead the design and construction process while robotic arms provide support. This approach represents an interesting new direction for construction.

Robotic Brick-laying

Brick has been a favored building material for centuries, but its potential for automated construction is a relatively recent development. Early research in architectural robotics delved into brick-laying, and the field has since explored interactive and augmented assembly methods. Das et al. (2020) tackled the challenges of interactive robotic brickwork, incorporating computer vision libraries, to select and evaluate materials with varying color tones. Meanwhile, Azambuja Varela et al. (2021) experimented with an automated wall-building process directed by an algorithm that reads, a hand-drawn curve, pushing the boundaries of brick construction even further.

While exploring the potential of robotic construction to create accurate, flexible, and adaptable structures on-site, outside the confines of factory settings, it is crucial to consider factors that impact the additive fabrication process of bricks. The process depends on the material deposited, component performance, and production speed. Bonwetsch et al. (2006.) examined digital design and fabrication with bricks as a building material, highlighting the simplicity of the process and its focus on material parameters. It was found that higher resolution can result in more detailed components with better functional properties, but it also slows down production and affects costs and overall design. With these insights, researchers continue to push the boundaries of automated brick construction, opening up new possibilities for the industry's future.

Multi-Objective Optimization

Multi-Objective Optimization (MOO) has become, a widely-used approach in building design due to the need to balance conflicting design criteria, such as energy consumption, thermal comfort, construction cost, and environmental impact. To identify the Pareto optimum trade-off between these objectives, MOO algorithms are employed.

A study by Bruun et al. (2021) employs a multi-objective optimization process to ascertain an optimal fabrication sequence that enhances the structural behavior over all construction stages of the masonry arch.

In summary, the integration of human-machine interaction, augmentation of robotic tasks using sensing, and MOO has enabled human-robot interaction (HRI), in construction processes. While perception and control are critical components of these systems, researchers are now focusing on incorporating advanced cognitive features, such as perception, event and activity recognition, and dynamic adaptation. Robotic construction with bricks as a building material has been explored in recent years, and several studies have demonstrated the potential of automated brick construction to create accurate, flexible, and adaptable structures on-site. The improvisational method, where humans lead the design and construction process while robotic arms provide support has also been proposed as an interesting new approach to construction. These developments demonstrate the potential for the effective integration of human input into robotic processes to achieve improved design performance and more efficient construction practices.

METHODOLOGY

In this paper, the authors present a closed-loop system that generates robot targets in turn-taking process during robotic operations through offline programming, which enables human involvement in design and fabrication procedures, resulting in a cyber-physical workflow (Figure 1). We demonstrate the optimized layer-by-layer placement of bricks using live interaction between human and robot to create a wall/arch structure.

This research focuses on developing, a collaborative robotic system for the efficient construction of masonry structures. The tool development involves the use of a vision-based system that uses Microsoft Kinect Version 2 (Zhang, 2012), and a pneumatic gripper attached to the end

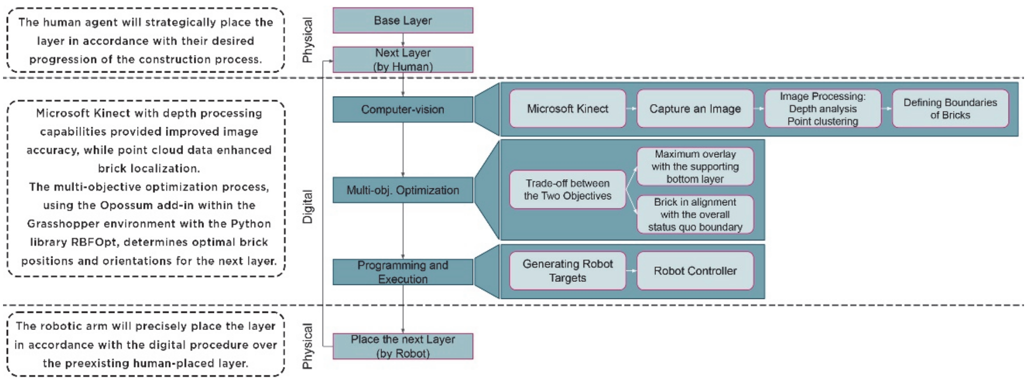

Figure 1
Cyber-Physical workflow of the implemented methodology

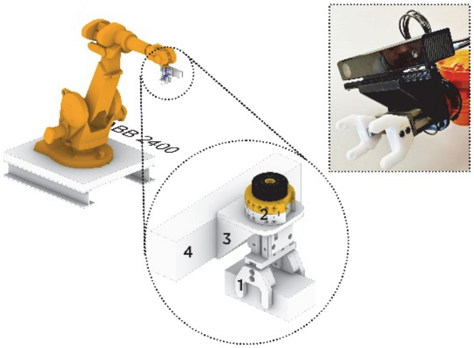

Figure 2
End effector with tool gripper and Kinect v2 RGBD camera as an integrated tool
1: Gripper, 2: Tool Changer, 3: Holder, 4: Microsoft Kinect

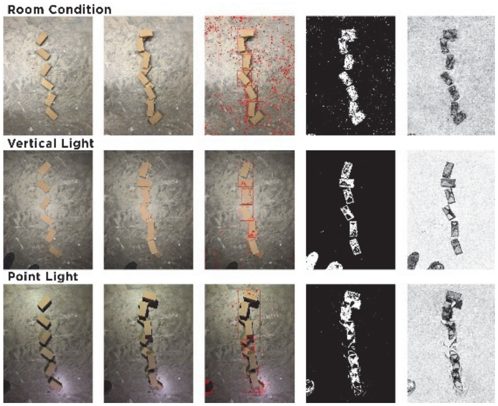

Figure 3
Image processing with OpenCV in different lighting conditions

of an ABB 2400 robotic arm for capturing the movement of the robot and the growth of the structure. For image processing, various scenarios were explored, to identify the most suitable approach for capturing the boundaries of bricks in the latest layer. The use of OpenCV and Microsoft Kinect with depth processing capabilities resulted in more accurate images and using point cloud data improved the localization of already laid bricks. The multi-objective optimization process is used to determine the optimal locations and orientations of bricks for the next layer, considering maximum overlay with the supporting bottom layer and aligning the brick with the overall boundary of the defined wall. The optimization process is performed using the Opossum (Wortmann, 2017) add-in within the Grasshopper environment, employing the Python library RBFOpt. Finally, the human-robot collaboration is established through a turn-taking process, focusing on achieving a reliable level of self-correction and capturing user intention. The output of the system provides rectangles for the next layer of the construction, while detectable rectangles serve as input for generating robot target in Grasshopper.

Tool development:

To capture the movement of the robot and the growth of the structure, we developed a vision-based system that uses Microsoft Kinect Version 2 and a pneumatic gripper, attached to the end of an ABB 2400 robotic arm, via a pneumatic tool changer. Figure 2 shows the end effector, which is capable of holding the Microsoft Kinect and the pneumatic gripper; and is always perpendicular to the ground, with the movement of the robot not blocking its vision.

Image processing:

The primary objective of image processing in this research is to capture the boundaries of bricks in the latest layer, which will then be used to optimize brick orientation in the subsequent layer. This process requires accurate image processing, as the placement of each brick in the next layer is heavily influenced by the bricks in the layer below. To achieve this, various image processing scenarios were explored to identify the most suitable approach for the research objectives. As illustrated in Figure 3, OpenCV was initially used to capture the objects in the latest layer and compute the line boundaries associated with each individual brick.

While this method provided a general understanding of the necessary image processing for this problem, it became evident that due to varying lighting conditions and the absence of depth processing; OpenCV alone was not suitable for this research.

Consequently, in the next step, Microsoft Kinect was tested for capturing more accurate images. Thanks to the depth processing capabilities embedded in Kinect, and using Tarsier add-in in Grasshopper to localize already laid bricks through point cloud data; extracting each layer boundary became feasible. As demonstrated in Figure 4, the extracted color clustering image shows high quality bitmaps, accurately representing the actual geometry.

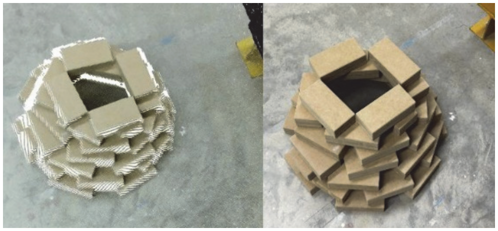

Figure 4
Color clustering image and difference between DSLR camera image and point cloud visualization extracted from Kinect.

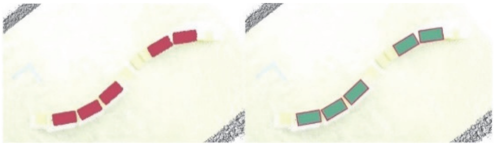

Figure 5
Clustering the points and extracting the boundary for accurate representation of already placed bricks.

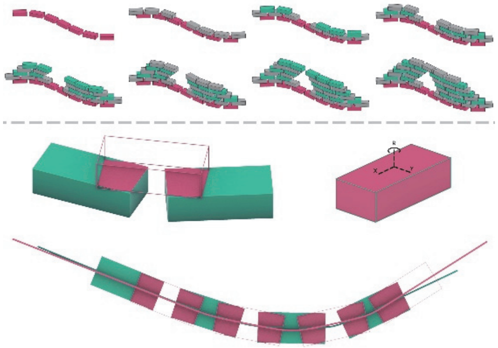

Figure 6
Top: Sequence of optimized brick-laying
Down: Maximum overlay and bricks alignment as two objectives.

In the next step, Python hard coding was required to extract the precise boundaries of each brick corresponding to a specific layer. As shown in Figure 5, this was achieved by aligning the extracted image with the actual 3D model and k-clustering data points to reveal the boundaries of all bricks in the layer. By taking one image from roughly above the work zone, the 2D surfaces will appear which representing the active layer extracted from the image processing phase, the multi-objective optimization process can now be performed to determine the optimal locations for the bricks in the next layer.

Multi-objective optimization:

The optimization process focuses on achieving two objectives: ensuring that a newly placed brick has maximum overlay with the supporting bottom layer and orienting the brick in alignment with the overall boundary of the defined wall (figure 6). The optimization approach involves finding a trade-off between these two objectives to generate the most optimal brick placement patterns. The result consists of the location and orientation of each brick in the XY plane. It is assumed that, due to the linear arrangement of similar bricks in each layer, the Z orientation for each layer is constant. Consequently, the current scenario does not account for variations in brick height in specific local areas. Thus, this limitation of the research can be addressed in future investigations. The optimization is performed using the Opossum add-in within the Grasshopper environment, employing the Python library RBFOpt for multi-objective optimization. The Opossum approach allows for the extraction of different acceptable design orientations that can be further explored and used to generate the final robotic code. To avoid overfitting and ensure optimal results, the optimization process is halted either when the iteration limit of 200 is exceeded or when no further improvements are observed in the optimization process for 20 iterations.

HUMAN-ROBOT COLLABORATION:

To discretize the computational representation of a block, we use XY coordinates and rotation around the Z-axis in our approach. The output provides rectangles for the next layer of the construction, while detectable rectangles serve as input for generating robot targets in Grasshopper. To measure reliability, we employ a multi-objective optimization approach that balances the need for precision with the desire for collaboration between robots and humans as part of a turn-taking process. We focus on achieving a reliable level of self-correction to capture user intention. In this project, we utilized half-blocks which needs to hard coding the robot, a task that was eliminated by ruling that only human agents are capable of. We found that by providing this opportunity to humans, they are now able to modify and edit the structure's form with even better resolution. As a result, there is no need to resort to hard coding, and human has allowed for more flexibility and accuracy in shaping the structure. Figure 7 illustrates the collaborative process between robots and humans in achieving a self-correcting level of construction.

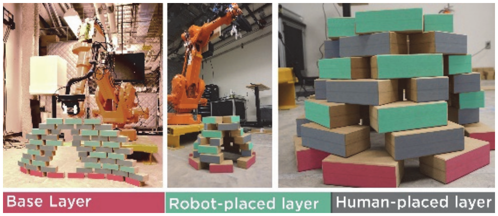

Figure 7
The sequence of human-robot collaboration

In this study, the authors present two constructed scenarios to test the effectiveness of a self-correcting workflow on two different structures.

Constructed Scenarios:

An optimized construction process has been developed to enhance the generation of robot targets for robotic fabrication using the Robots add-in in the Grasshopper environment. Specifically, the process involves image processing to enable the robot to pick up blocks from a feeder and place them in a defined location. Unlike the regular method provided by the default setting of Robots add-in, the optimized approach incorporates all necessary rotations of axes during the transportation of blocks to the feeder, thereby ensuring correct block orientation. Additionally, the height of the robotic arm's end effector is maintained at a constant level that is only two blocks higher than the previous layer, resulting in a speed improvement of over 25 minutes compared to the regular method. The image capture height is fixed at the home position, which is defined as the initial and final point of each brick-laying process. This design choice eliminates the necessity of adjusting the angle or height of the computer-vision system for each layer, and obviates the requirement for system calibration. It is important to note that the placement of the base layer must be within the accessible zone of the robot and the developed tool, and must not exceed the borders of the area captured by the Kinect camera.

The proposed new method, workflow, and human-robot turn-taking collaboration were tested in a wall construction scenario to demonstrate the potential of achieving a self-correcting construction process. Specifically, a wall with a free-form base layer was constructed, and the human user intentionally excluded one block in the second layer to create an opening. It is worth mentioning that the base layer should be placed within the accessible zone of the robot and the developed tool, and it should not exceed the borders of the area captured by the Kinect camera. The optimization procedure aims to attain two key objectives, namely, maximizing the degree of overlay between a recently placed brick and the underlying supporting layer, and aligning the brick's orientation with the overall boundary of the specified wall. To generate the most optimal brick placement patterns, the optimization technique involves striking a balance between these two objectives through a trade-off analysis, while pursuing the opening created by the human agent, as shown in Figure 8. The user later decided to close the opening, and the system

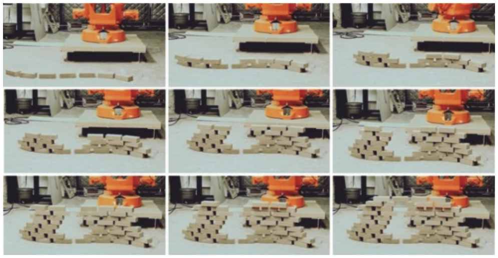

Figure 8
Wall that includes a spline as a base layer with an opening

continued the closing process, with the user modifying the robot-made layer using two half-blocks to achieve a preferred shape. This proactive human-robot collaboration successfully demonstrated the self-correcting construction process.

In this study, authors explore the potential of a computational system to optimize construction by adapting to changes. The system's optimization approach involves finding the most optimal brick placement patterns while taking into account the scanned layer's geometry and overall boundary of the defined wall. While the system can somewhat capture the design intention posed by the human agent, its optimization approach primarily relies on the scanned layer's information to place the next layer.

Authors tested the system in two scenarios, where the human agent created an opening in one layer, and the system followed suit by making a larger opening in the next layer. The user modified the third layer using half-blocks and capped the opening in the fourth layer. The system continued to pursue this approach, and after six layers, a structurally stable dome was constructed (Figure 9). These experiments aimed to showcase the system's interactive and adaptive nature and its potential to optimize construction while catering to changes.

Figure 9
Dome as the second scenario with an intentional deviation.

The whole system can be seen as an interactive and adaptive computational system that aims to optimize construction for set parameters and adapts to changes interactively. The results highlight the potential of such a system to optimize construction while catering to changes, ensuring the final result aligns with the concept of self-correcting construction and multi-objective optimization.

DISCUSSION

The proposed workflow demonstrates the potential of human-robot collaboration in construction, specifically in the context of brick-laying. By integrating a vision-based sensing framework and multi-objective optimization method, we were able to achieve adaptive and interactive manipulation capabilities in the pick-and-place task. Our results show that the multi-objective optimization model is a promising adaptive design driver during assembly. However, there are several limitations to the methods employed in this research.

Firstly, the scanning occurs in 2.5D and only looks down on the assembly, which makes the data prone to camera lens distortion. Extrinsically calibrating the system and utilizing a larger freedom of movement could mitigate this issue. Secondly, there is no integration of multiple images to smooth out sensor noise. While we worked around this issue by fitting bounding curves, it definitely impacted the overall precision. Thirdly, the discretization of bricks for optimization relies on a highly abstracted representation of what we captured. This approach inherently assumes perfectly planar build surface/layers and may fail in a real construction setting.

In addition, the sensor used is primarily for entertainment and has been shown numerous times to be fairly inaccurate, especially at larger distances. Using a sensor like an Azure Kinect, which has wide and narrow field of view sensors, could greatly improve precision. Furthermore, the optimization pipeline we presented in this paper relies on the assumption that the most stable way to lay bricks is to have maximum overlap, and it is hard to capture the overall structure's design intention. Therefore, the system's reliability in constructing the wall structure without compromising its stability is questionable, and active measures must be taken to mitigate the negative effects of this approach.

In future studies, we need to evaluate the system's robustness to real-world uncertainties and variations in the construction site. Incorporating turn taking sensing and feedback loops could improve the system's adaptability to changes in the environment and increase its reliability. Moreover, since we relied on a digital representation of the environment, the accuracy and completeness of this representation can affect the effectiveness of the optimization method. To address this, intentional geometric discretization of certain elements, such as top layer bricks, can improve the optimization's performance.

Despite these limitations, our research provides a foundation for exploring the potential of human-robot collaboration in construction, particularly in pick-and-place tasks. While our research is adaptive and interactive, we acknowledge that it is not truly collaborative, and future research should focus on defining interaction and collaboration modalities. Additionally, extending this approach to other building materials and construction processes and investigating the potential of human-robot collaboration in other phases of construction, such as excavation, site preparation, and finishing, can be valuable. Overall, the presented research contributes to the evolving vision of construction robotics and demonstrates the potential of collaborative robots to address the challenges facing the construction industry.

CONCLUSION

In conclusion, this paper presented a novel methodology for enabling human involvement in the design and fabrication of structures through a closed-loop system that modifies or generates robot targets in a turn-taking process during robotic operations. The proposed workflow resulted in a cyber-physical approach to fabrication that demonstrates optimized layer-by-layer placement of bricks using live interaction between human and robot to create a wall/arch structure. The developed vision-based system, multi-objective optimization process, and human-robot collaboration approach were tested on two constructed scenarios, which demonstrated the effectiveness of the proposed methodology. The proposed approach improves the accuracy and reliability of the robotic fabrication process, while also providing opportunities for human creativity and intervention. Future investigations may address limitations such as variations in brick height in specific local areas and expand the proposed methodology to other types of structures beyond the tested wall and arch scenarios.

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