Multi-Robot Collaboration for 3D Concrete Printing

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Abstract

Digital concrete fabrication, i.e., 3D Concrete Printing (3DCP) as an emerging technology, provides various advantages, including design freedom, reduced material waste, and increased productivity and safety. Beyond these benefits, 3DCP addresses pressing construction challenges such as low productivity, a shortage of labor, and an aging skilled labor force. 3DCP involves a blend of manual tasks (e.g., placing electrical boxes, steel support, and reinforcement) alongside printing. Typically, the 3D printing crew concurrently manages printing and auxiliary activities, such as installing non-printed components. This crew often conducts visual inspections of the printed layers to identify deformations and defects. These additional tasks may divert the crew's focus from the primary responsibility of overseeing the 3D printing system. Additionally, these manual tasks expose the workers to dangerous situations, especially when working closely with the extruder of the printing robot. The 3D printing process only automates the concrete deposition, but all other activities remain as manual tasks, exposing workers to work closely with the extruder of the robot printer. To mitigate this issue, we foresee further automation in 3DCP, integrating an assistant robot for placing non-printed components without the need to stop the printer process or expose workers to be struck by hazards. These robots would be operating concurrently with the printing process automating the auxiliary task and minimizing the disruptions to the printing process. This will mean that the crew can concentrate more on the quality and efficiency of the printing process without having to put themselves in harm's way or worry about spending time placing fixtures.

Motivation

The construction industry represents a global annual worth of $10 trillion but is facing pressing problems like skilled labor shortage, little implementation of technology, and almost zero productivity growth [1]. These problems are more notorious in developed countries like the USA where the workforce gap is slowing down the construction industry. Just in 2017, almost 200,000 jobs in the construction industry remained unfilled [1]. There is a pressing need for the construction industry to increase the level of automation with robots. One plan to automate the industry is to start with conventional building activities (e.g., bricklaying, painting), but also another approach is to create completely new construction methods like 3D concrete printing [1]. All these new construction methods automated with robots are typically described as digital fabrication or construction robotics.

Construction robotics is a reality, and the industry has started to accept more applications where robots are the key to increasing productivity and having an impact on safety, quality, and cost [2]. For instance, robots have been successfully implemented in activities such as concrete drilling [3], drywall framing and sheathing [4], material handling, scaffolding assembly, autonomous driving of heavy equipment, inspection with robots (i.e., drones, wheeled-based, and quadruped robots), and layout mobile robots [5].

Multiple limitations slow down the adoption of robots in the construction industry like the high cost of implementation, the fragmented nature of construction, the incompatibility with existing workflows, and most importantly, the immaturity of robotic technologies for the construction market [6]. Since robotics in construction is an emergent trend, it is better to first understand how other industries are implementing robots in their domains.

Industrial robots have a dominant presence in other markets, but in the construction industry, this is just a starting trend. For instance, in 2023, for the second consecutive year, the annual installation of industrial robots has exceeded the mark of 500,000 units; and the major industries leading the implementation of industrial robots are automotive and electronics [7]. In contrast, the number of robots in the construction industry is expected to exceed only 7,000 units by 2025 [6]. However, this is an increasing trend that will continue in developed countries like the USA where there are concerns about labor shortage, accelerated aging workforce, and considering that construction is one of the most dangerous industries with half of the deadliest jobs in this country.

Industrial robots and Collaborative Robots (Cobots) or in general robotic arms (RA) have been extensively investigated for multiple applications in the construction industry. For instance, robotic arms have been investigated or utilized for interior wall painting [8], façade assembly [9], concrete drilling [3], panel framing [10], drywall sheathing [11], false ceiling installation [12], and laying CMU blocks [13]. However, all previous work focuses on replicating a traditional construction activity, but a more innovative approach is recreating a completely new construction method like in the case of 3D Concrete Printing (3DCP).

Additive Manufacturing of Concrete (AMoC) or 3DCP is a digital fabrication technique that utilizes a digital model to extract its geometry and generate instructions to command the kinematic of a robot printer with an extruder tool attached that will deposit a cementitious material layer by layer to generate a physical product or building component [14]. The potential of using 3D Printing technologies for Architecture, Engineering, and Construction (AEC) has been studied previously by multiple researchers. The benefits can be summarized as a positive impact on construction productivity and the project's sustainability. Regarding productivity, three aspects make possible the increment in efficiency. The first aspect is the elimination of formwork or layout activities [15], the second one is the automation of the printing process with robots [16], and the third aspect is the overall reduction of labor needs [17]. On the other hand, the factors that improve the project sustainability are the reduction in material waste [18], the optimization of the material needed [19], and the reduction of CO_2 emissions [20].

There are two main approaches for 3DCP construction regarding the printing location, on-site and off-site 3DCP construction (Figure 1). On-site 3DCP refers to construction methods where structures are printed in situ. On the other hand, off-site 3DCP refers to the process of printing the structural prefabricated components in a different location to the site in a controlled environment, typically in a factory. On-site 3DCP typically deals with challenges related to an uncontrolled printing environment, delays, extra costs, and the time needed for 3D printer installation [21]. On-site 3DCP will have the extra cost and time for delivering and installing the printer but also will save time regarding the assembly of 3D printed pieces on site and provide a better structural behavior for printing a monolithic component. In contrast, off-site 3DCP will save time regarding the printer delivery and assembly but will increase the time and cost for delivering all the 3D printed components to the job site and extra time and cost for the assembly of the structure once all the 3DCP components are on site.

Large-scale 3D printers can be classified into two main categories: robotic arm printers and gantry systems. Robotic arms typically have six degrees of freedom meanwhile gantry systems only have three or four degrees of freedom. Robotic arms are easily available, not too expensive, have higher accuracy and the kinematics are easy to control with the manufacturer's software. Also, if they are provided with external axes like rail systems, lifters, or a moving base with wheels and tracks. Gantry systems are ideal for printing large-scale monolithic buildings, and robotic arms are ideal for individual elements [22]. Then robotic arms are a more flexible approach for 3DCP construction since they could work for off-site construction and on-site construction without the need to be confined by a footprint area like a gantry system.

(a) (b)

Figure 1. On-site (a) and off-site (b) 3DCP construction using robotic arms. Source: CyBe Construction.

Considering all these benefits that 3DCP technologies can bring to the construction industry several applications have already been identified and implemented in the AEC industry. For instance, 3DCP is a potential solution for the housing shortage in the world [23], mitigating the impact of labor shortage in developed countries with an aging skilled labor population [17]. Other applications involved developing human settlements in remote areas with difficult access [24], the construction of military facilities for the war zone [25], the creation of shelters for populations affected by a natural disaster [26], or in a more futuristic application, the construction of human settlements in an extraterrestrial environment [27].

But 3DCP technology is not the solution for all types of construction projects, it has benefits but also limitations for projects with a traditional design that do not exploit the maximum potential of the geometry freedom and topology optimization of the material. There is also misleading information that reports that this technology will decrease construction cost and time, but this is only true in specific conditions of the construction project. For instance, just comparing the printing time with the whole construction of the project is a common misleading compassion found in the literature without considering all the extra time needed to install other building elements such as the roof, floors, windows, MEP, and other building components [28]. All this misleading information can be detrimental to the 3DCP industry, giving false expectations to new investors and contractors. Then there is a pressing need to continue automating the other activities that complement this technology (e.g., steel reinforcement, MEP rough-ins, and steel printing supports).

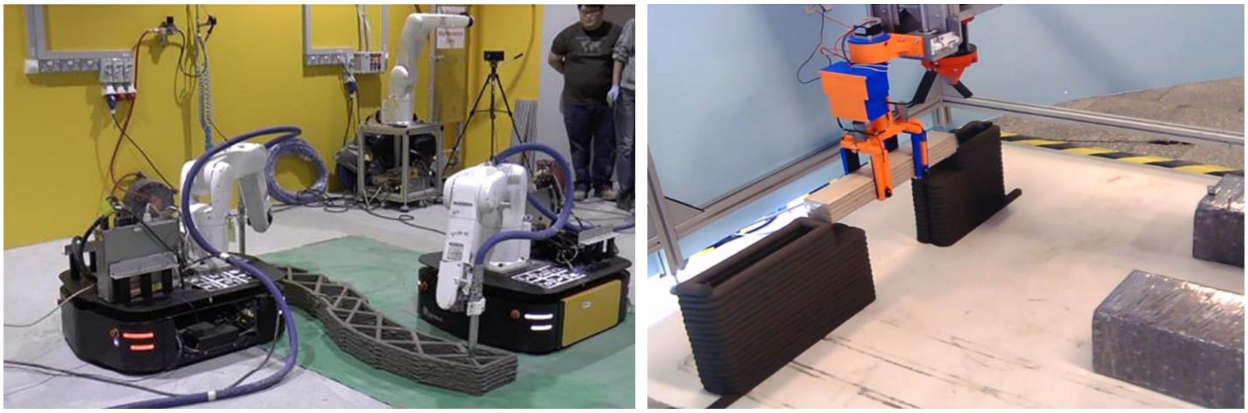
Problem & Background

Utilizing 3DCP does not maximize the potential of digital fabrication since a large portion of the remaining activities are still not automated. For instance, activities during the printing process, and all postprocessing activities are still depending on the labor force. Also, since many of these activities depend on human-robot collaboration, the quality, and safety of the project are prone to human error. One important safety and quality consideration is that the extruder attached to the robot printer might have some limitations regarding starting and stopping the printing process. Starting and stopping the extrusion is not recommended since it can create air bubbles in the extruder and generate unprinted gaps in the extruder layers (filament splitting as shown in Figure 2), or even worse create clogs between the pump and the extruder [29]. Under this consideration typically one criterion for defining the printing path is to minimize these interruptions and maximize the continuity of the printing path as well as the continuity of the printing operations. These situations also generate the problem that the 3D printing crew needs to consider extra personnel for installing all the printing supports and accessories needed while printing.

(a) (b)

Figure 2. (a) Filament splitting due to the pumping system clogged (PERI 3D Construction. (b) Filament interrupted because of air bubbles on the extruder.

Contributory activities during the printing process are a pressing problem in the 3DCP industry since extra personnel need to be allocated exposing them to a struck-by hazard by robot printhead, and the printing crew can get distracted from their main task which could be detrimental to printing quality of the 3DCP building components. However, since 3DCP is still an emergent technology, there is a big gap in the study and limited attempts to address this problem have been found in the literature. Multi-robot collaboration is an alternative with immense potential to take care of all the activities, not yet automated in 3DCP projects. For instance, previous research has explored 3DCP with a team of mobile robots as shown in Figure 3a [30], or has explored the idea of using a lintel gripper for 3D-printed walls doorways, and window openings as shown in Figure 3b [31].



(a) (b)

Figure 3. Multi-robot collaboration for 3DCP. (a) Team of mobile robots for printing. (b) Lintel griper for 3DCP.

The 3DCP industry has also explored this problem by mostly relying on methods that involve having personnel dedicated to these activities during the printing process, postprocessing, or in some cases having an external robot to assist the robot printer. The assisting crews during the printing process might involve activities such as curing concrete (Figure 4a), correcting defects on printed layers (Figure 4b), installing steel mesh support (Figure 4c), material moisture control (Figure 4d), surface finishing (Figure 4e), and installing MEP rough-ins (Figure 4f).

(a) (b) (c)

(d) (e) (f)

Figure 4. Contributory activities for 3D Concrete Printing involving a dedicated crew. (a) Concrete curing, (b) layer correction, (c) steel mesh ladder installation, (d) temperature control, (e) surface finishing, and (f) electrical box installation.

Some of the main post-processing activities that oversee a dedicated crew may include core drilling holes for passing MEP pipes (Figure 5a), saw cutting wall cutouts to fit plumbing and electrical fixtures (Figure 5b), shoring long span overhangs (Figure 5c), and wood framing in doorways and roof (Figure 5d). On the other hand, the activities that have been attempted for automation using another robot include window installations as shown in Figure 6a, robot installation of mechanical connectors for reinforcement, as shown in Figure 6b [32], and modifying the extruder shape to allow printing around a preinstalled steel mesh for the wall reinforcement, as shown in Figure 6c [33].

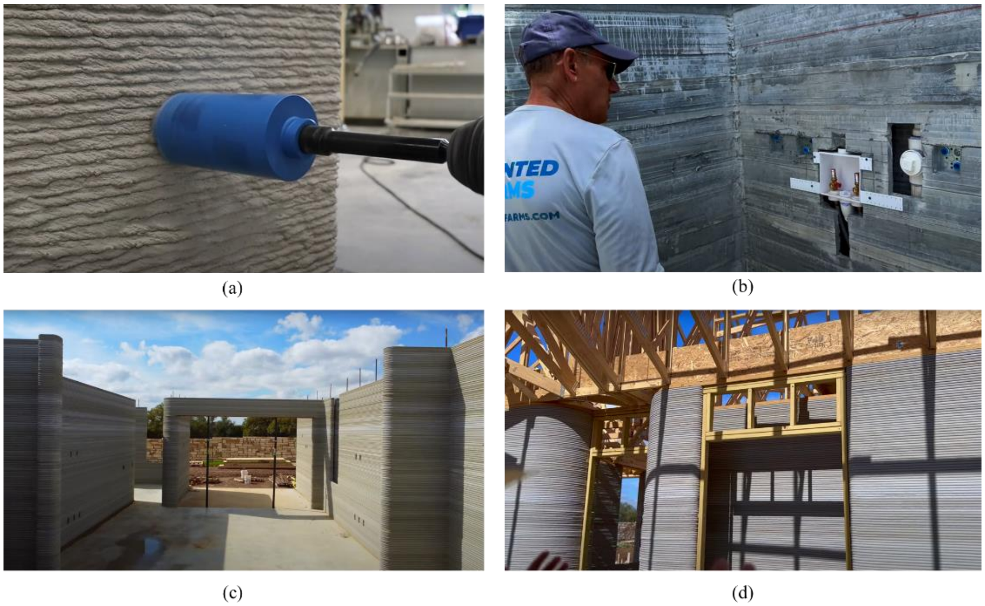


Figure 5. Post-processing activities with dedicated crew. (a) Core drilling passes, (b) saw cutting MEP wall cutouts, (c) shoring long spans, and (d) wood framing for openings and roofing.

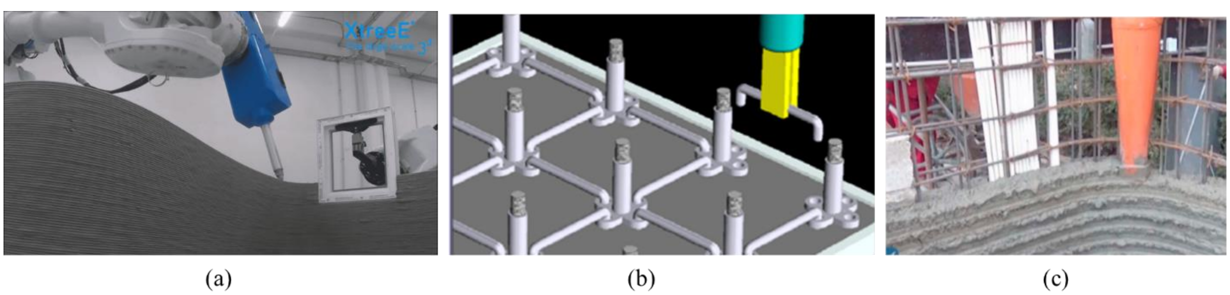


Figure 6. Automated contributory activities during printing process, (a) windows installation, (b) mechanical steel reinforcement connectors, and (c) steel mesh reinforcement.

From all the activities identified in both literature and practice, the activity with the best feasibility for automation and the largest impact on the printing process is the installation of shutters to avoid core drilling passes on the 3D-printed walls. Passes in a 3DCP wall are something inevitable if the product and process are not designed properly. Fortunately, 3D printing allows the design flexibility to adjust the printing path accordingly but still a collaborative robot is needed to pick and place different shapes of passes and avoid core drilling the wall. Core drilling a wall is not only a nonproductive activity but also is considered a non-quality task that could comprise the structural integrity of the 3D printed component. Also, matching the right size and shape of the passing with the necessary box, pipe, or ductwork is important for saving time and material in the posterior sealing or calking activities during the finishing process of the building. In some cases, even the use of fire protection products for isolating or compartmenting different rooms will be required and those materials will increase the cost significantly if the gap between the passing cutout and the passing conduit is larger.

Some of the most common pass types in vertical building components, like 3DCP walls, involve circular shapes, square shapes, and rectangular shapes. Typically, circular shapes are used for pipes (e.g., water, sewage, rainwater, air conditioning drainage, gas distribution, and electrical cables). Square shapes are more common for electrical boxes, and rectangular shapes are present in a larger variety of use cases (e.g., electrical boards, air conditioning ductwork, electrical trays, valve compartments, etc.) Figure 7 shows some examples of shapes and applications of passes in buildings.

(a) (b) (c) (d)

Figure 7. Different shapes and applications for 3DCP cutouts, (a) circular, (b) rectangular, (c) plumbing, (d) electrical. Source: Mudbots

Method

The methodology followed for this report consists of implementing a simulation that resembles an off-site 3DCP operation that is mass-producing building components. These building components are mainly vertical load-bearing walls that in a posterior phase will be assembled on-site for a housing project. The scope of this report solely focuses on the automation of the off-site mass production of the building components in a 3DCP plant. This approach is becoming common in the construction industry since off-site operations in a 3DCP plant allow better control of the environmental conditions, better quality control, and avoiding a rough environment like traditional on-site construction. Figure 9a shows the controlled conditions of a 3DCP off-site production plant and Figure 9b shows the assembly process of the produced wall components on-site. The scope of this report solely focuses on the offsite 3DCP production.

(a) Off-site storage of 3DCP walls

(b) Assembly on-site of 3DCP walls

Figure 8. Off-site and on-site operation for 3DCP wall components

Typically, these 3DCP wall components are hollow and only the shell of the wall is printed which is very convenient for allocating rough-ins and sometimes even insulation material like foam. However, this implies the consideration of cutouts or openings in the 3D-printed wall that will enable the next crews to allocate different complementary conduits and systems. The most common installations involve plumbing pipes, square electrical boxes, and rectangular ductwork for mechanical systems. For this report, the three main classes of openings were considered, and using an image processing system the images of the different shapes will be captured for machine vision processing that will allow identifying the type of opening. Figure 9 shows several different pipes and ductwork penetrations that could be found typically on construction projects.

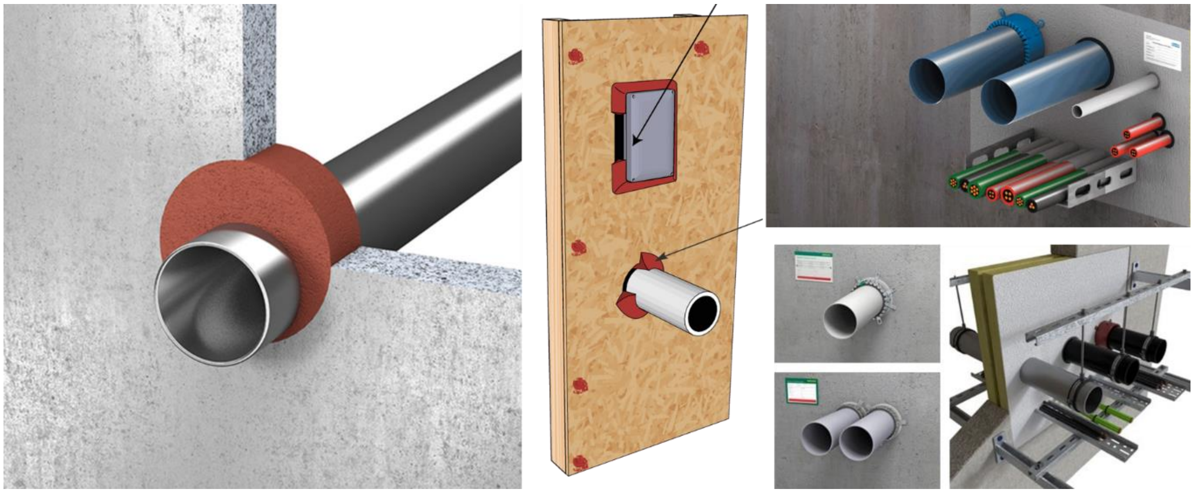


Figure 9. Pipes and ductwork penetrations or openings that could be found in construction projects.

Fresh concrete material needs shoring support at the bottom of the current printed layer to continue depositing the next layers. In case of a gap or an opening in the printing layer then is required to install a block out with the corresponding shape to fill the gap before resuming the printing process. This process, if it is not automated, implies that someone will have to manually install the corresponding block out. This manual approach is not ideal since will involve having dedicated personnel for this simple task, also it is prone to human error, and in the case of inline installation may create a hazardous activity since the worker might be close to a robot printer or other mechanism (conveyors).

A simulation environment was implemented using CoppeliaSim for selecting the proper block-out shape and then installing it in the corresponding 3DCP wall. The implemented environment involves a robot printer, a cobot for installing the block-outs, a system of conveyors for feeding the cobot with block-outs, a system of conveyors to move the 3DCP components close to the cobot, and a camera system for capturing images of the 3DCP wall opening. The robot printer is an ABB IRB 4600, and the cobot is a UR10. Figure 10 shows the layout of the simulation environment for this task.

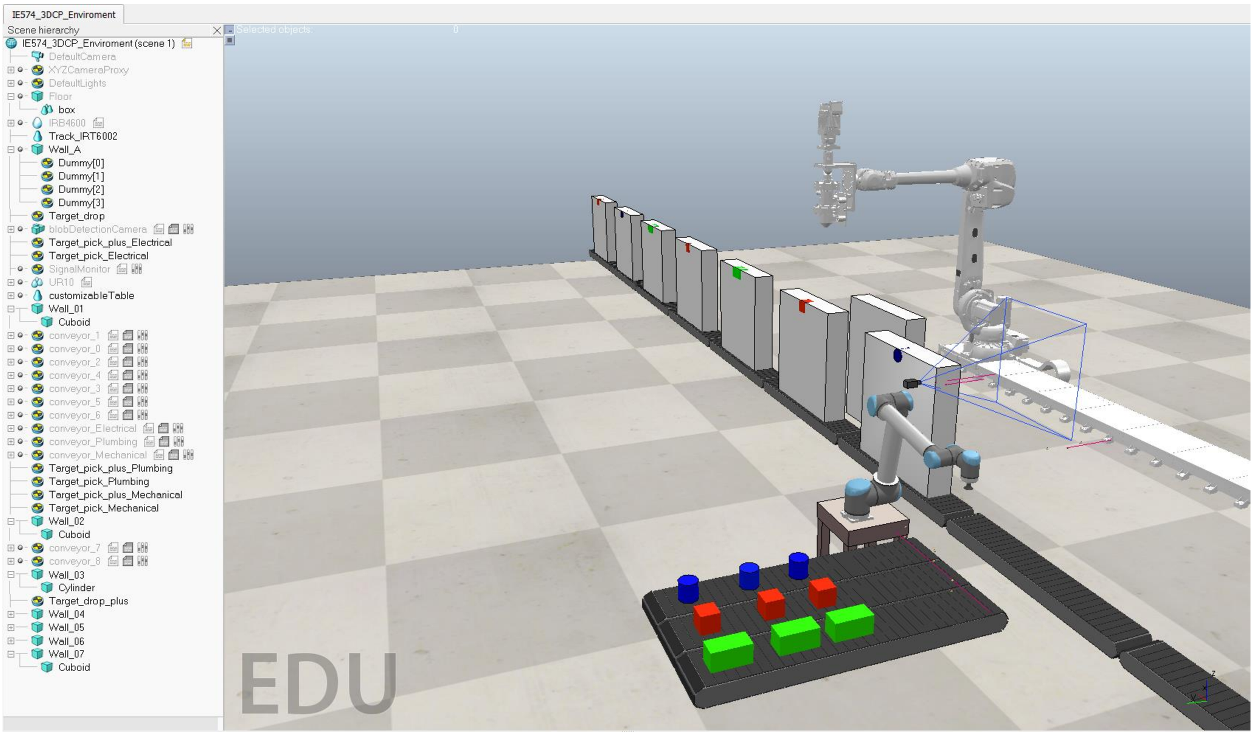


Figure 10. 3DCP Off-site plant simulation environment

The ABB IRB 4600 uses a path planning file to define the toolpath of the current wall that later will be moved using a conveyor system once the printing layer is finished until the top of the block-out gap is finished. For this task, a "CSV" file was created to define the toolpath of the extruder. The IRB 4600 robot has attached an extrusion tool that is an actual 3D concrete extruder and the new TCP coordinates have to be used using frame transformations to define the new tool TCP frame. For this, the IRB 4600 robot came from the library without any tool but using Rhino 7 a CAD modeling software the mesh required to be imported to CoppeliaSim was generated. Figure 11 has a view of the actual tool and the digital replica in Rhino 7.

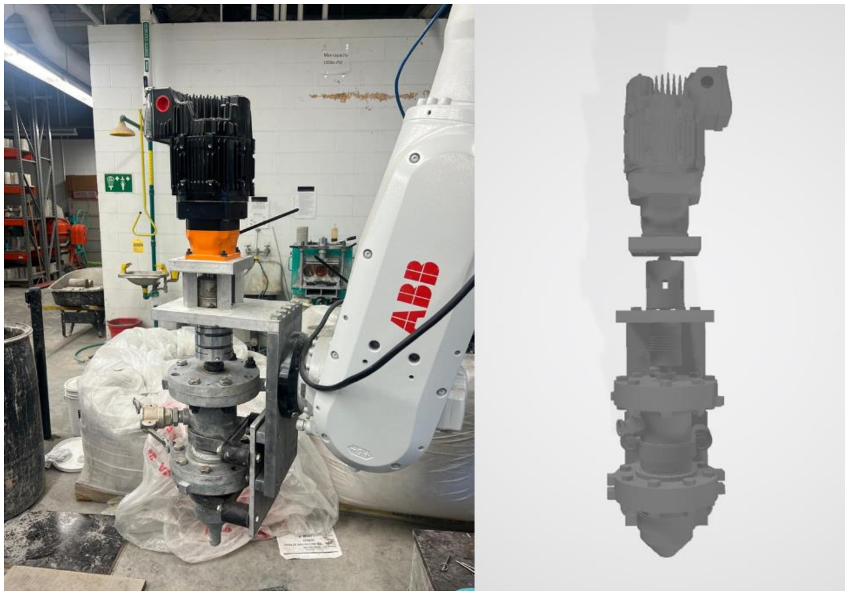


Figure 11. 3D Concrete Extruder tool for industrial robots

For this task "Dummy" objects were located in the vertices of the printed wall to identify the location of this wall and then feed the "csv" file of the printed wall. Also, the ik_Tip of the robot's last link was modified to extend the printing length of the concrete filament and be able to print the desired height of the wall keeping it visible. Figure 12 shows the objects in the hierarchy, the robot printing simulation, and the ik_Tip code.

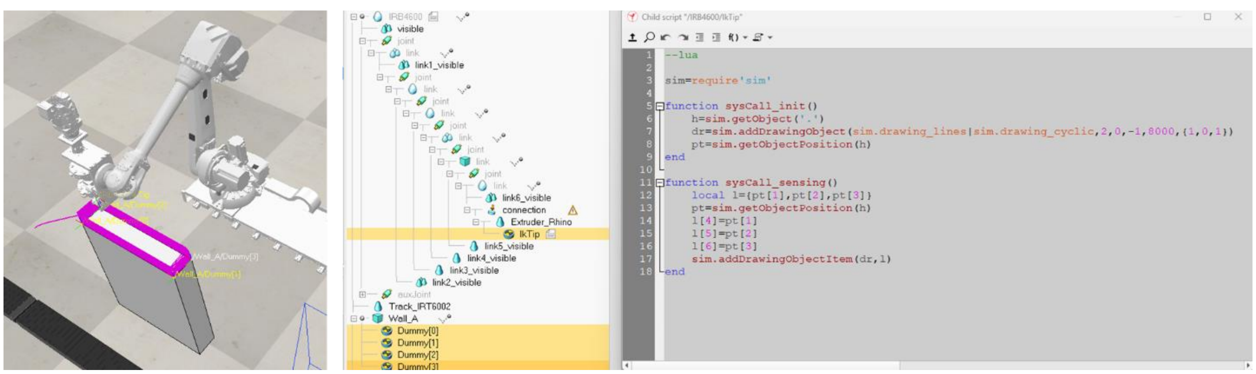


Figure 12. 3D Concrete printer toolpath planning

For the pick and place task using the UR10, the process consists of using sensors that send signals that will activate different tasks in the simulation. There is a "Proximity_sensor" that commands the camera to capture an image of the wall when it reaches a position where the gap or hole is approximately centered in the camera view. The next proximity sensor is located in the conveyor and activates the UR10 to start picking the right conveyor based on the image processing of the camera image and positioning close to an approaching target that will be ready for the wall when reaches through the conveyor the position. Then the last proximity sensor will activate the last movement to reach the target and drop the object inside the wall gap. A conceptual map of the overall process and communication is shown in Figure 13.

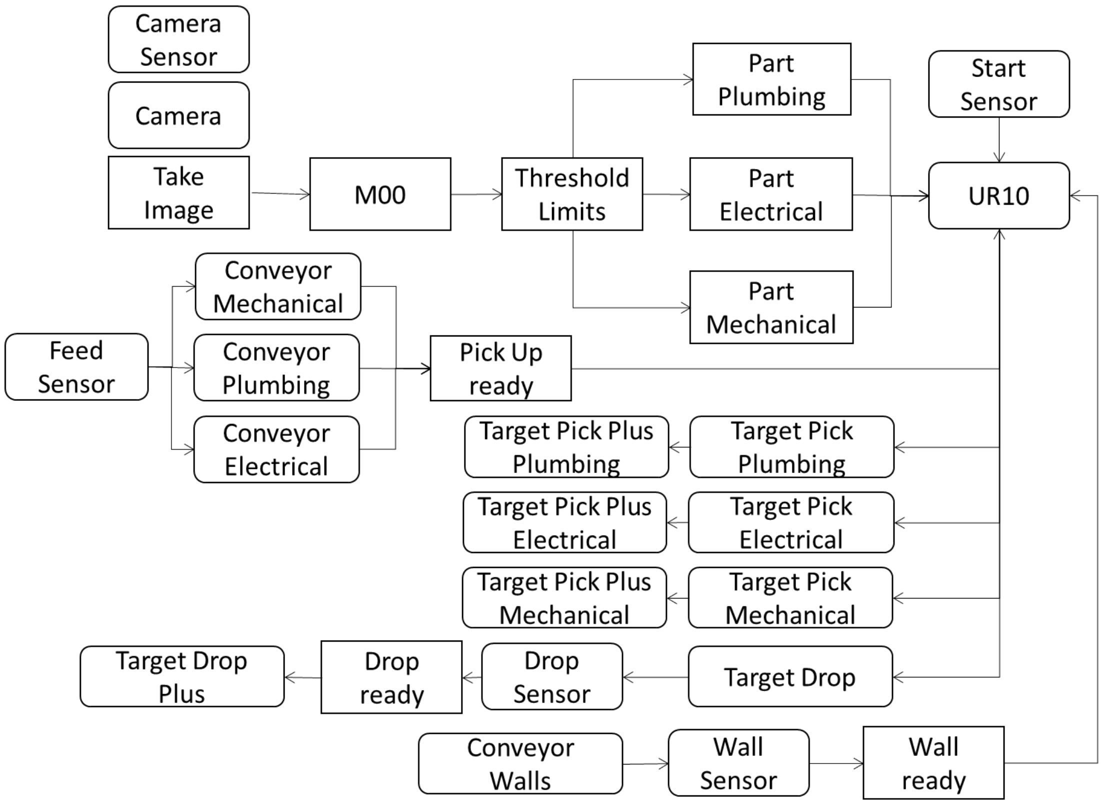


Figure 13. Flow chart for Robot Simulation of UR10, camera, and proximity sensors.

First, a proximity sensor activates the camera and captures an orthographic image of the wall when the wall opening is approximately centered for the camera. The captured image is then converted into a black and white image using the 150 values of intensity as a threshold to divide the pixels histogram as black or white. Next, the zero moment "M00" is computed and based on thresholds defined (min and max) for each category (i.e, circle, rectangle, square), the values are used to send a signal for the corresponding pat type (i.e, "part_electrical", "part_Plumbing", "part_Mechanical").

A second proximity sensor, after taking the image, sends the signal to UR10 to begin the kinematics to pick the target in the corresponding conveyor belt depending on the value type of the "part" signal when the proximity sensor of the wall indicates that the wall is ready to start picking the block out. In addition, the code checks that the conveyor feeder has the object ready to pick up with a corresponding proximity sensor. Then, the UR10 will move to an approach point close to the wall waiting for a new signal that indicates that the wall is in the right position to move the object into the wall and drop it. Figure 14 shows a representation of the three options of objects images taken.

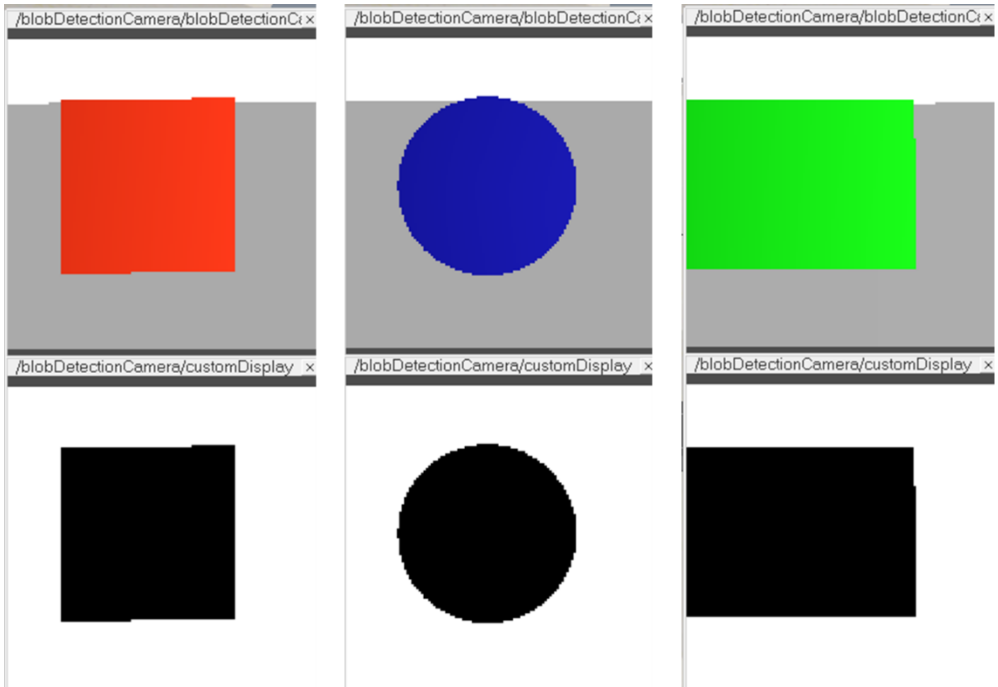


Figure 14. Figures images for classifying based on M00

To fully use machine vision to pick up the corresponding fixture we will need to integrate deep learning within this system. The camera will be able to take the image but for there to be a decision made for which fixture it is seeing we will have incorporated this type of learning. The system will autonomously take an input image from the camera sensor that can be used to determine what the robot is truly looking at. This will be used as the input to the deep learning model. The model we selected is a Convolutional Neural Network based on a Residual Network (ResNet). A ResNet is a model structure that addresses the problem of training very deep neural networks. The problem associated with the more complex input data you provide is that more and more layers are needed to create the connections to appropriately match input data to a desired output. Adding layers or even nodes to the layers can solve this issue by making the network more complex but this will in turn make the training more difficult. Additionally, networks can start to suffer from the vanishing gradient problem, where gradients will get exponentially smaller as they back propagate through the many layers of the model, making the training very intensive and more difficult. What the ResNet allows us to do is skip connections. This means the network can learn to bypass one or more layers. This is shown below where the arrows represent the skip connections that a sample ResNet has incorporated.

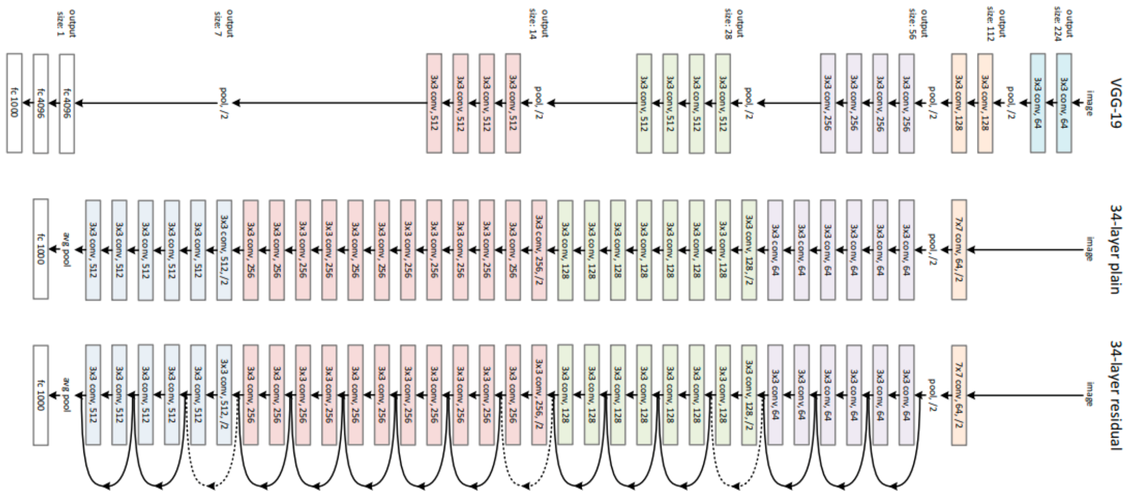


Figure 15. Network Model of ResNet34 showing Skip Connections

The use of ResNet lies in the fact that when you want to make a very generalizable model, it is very good at making the adjustments needed for more complex inputs, or a greater number of classes. Since we have created a simpler setup for our 3D concrete printing fixtures, with only 3 choices, we can make sure that our model will be prepared if more types of fixtures are added. The ResNet allows for more efficient training of deeper layers. Additionally, the skip connections are very good at improving the generalization of the model and allowing it to perform well on data it has not seen before.

Main Findings

In the case of making the decision on which fixture to choose based on the input image, two approaches were used. The first method used was a calculation of the central moment of the fixture taken from an input image. This method was highly effective for our usage case. With only three different fixtures present in our simulation there was an exceptionally large difference between the calculated zeroth-order moment (M00) calculation done. This meant that it was very straightforward for the Cobot to decide on which fixture to then grab from the conveyor belt. During our initial setup of the simulation, we set all three different fixtures on their own conveyor belts. This helped with this method because the cobot knew exactly where the fixture was needed. There was no need for additional machine vision or decision-making once the fixture had been identified. The fact that we set up our system with only 3 fixtures was the reason we could do this.

If this was a real-like scenario that had many more fixtures, all of which were not perfectly organized, we would need to devise another way to determine where to choose the correct fixture from. This would be done more easily with an additional machine vision system connected to a deep learning model that could parse through many different fixtures and locate the correct fixture out of the bunch. We were able to train a model that could do this very thing. Using a Deep learning model based on the ResNet model and finetuned according to our data set, we made another method to choose which fixture was needed. We saw success in training our model to a training accuracy of around 95% as shown in this graph here. We were able to achieve a validation accuracy of 90% as well.

Figure 16. Accuracy of the ResNet Deep Learning Model

The model itself required some finetuning of hyperparameters. The number of epochs was kept around 100 to allow for sufficient data training. Also, two more layers were added to the base model to allow the model to be optimized for our data set. The model architecture is shown below. Unfortunately, because the ResNet is a preset network, the shape of the base model is not shown, but the input layer was set to 128, 128 to match the training image size. We verified that the different layers did have trainable nodes by viewing the number of trainable parameters of the model, which is around 23 million. This is comparable to the number of parameters used from the ResNet which is also around 23 million.

Layer (type)	Output Shape	Param #
resnet50 (Functional)	?	23,587,712
conv2d_350 (Conv2D)	?	0 (unbuilt)
conv2d_351 (Conv2D)	?	0 (unbuilt)
max_pooling2d_175 (MaxPooling2D)	?	0 (unbuilt)
flatten_175 (Flatten)	?	0 (unbuilt)
dense_537 (Dense)	?	0 (unbuilt)
dense_538 (Dense)	?	0 (unbuilt)
dense_539 (Dense)	?	0 (unbuilt)

```
Total params: 23,587,712 (89.98 MB)
Trainable params: 23,534,592 (89.78 MB)
Non-trainable params: 53,120 (207.50 KB)
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Figure 17. ResNet Deep Learning model architecture

Also, the classifier was compiled with an Adams optimizer set to a learning rate of 0.001. This was found to be a good way to solve the loss and measure the amount of learning that was taking place. Early stopping criteria were also implemented to fight some of the effects of overfitting that was taking place with such a small number of classes. This early stopping criteria was made to have a patience of 10 to catch any instances of the model getting stuck at the same accuracy. With these changes to the model, we were able to make an accurate model that could be trained easily to our training set.

Evaluation

The application of zero order moments M00 was ideal for a simple scenario like the one selected where only three types of holes were defined (circles, squares, and rectangles). However, in reality, the spectrum of possibilities would be much larger. For instance, the pipes could be of different diameters, the electrical boxes could be rectangular or octagonal and from different dimensions, and the doctor or electrical trays might be from a large variety of sizes. The main advantage of this approach is that it is easy to customize in case new shapes need to be added and is very flexible to adjust for new shapes.

The location of the holes was predefined in the same height for all the walls, but this might not be always the case. Typically, the height for an outlet or a switch is standardized and regulated in building codes, but it might be a set of different heights in one single housing project. This problem was not addressed in the simulation, but this could be solved with a different, more robust implementation where the location of the object is determined using computer vision techniques. In this case we just focus on a classification approach but not on localization or objected detection. In future work this could be implemented to determine a more robust approach that allows detecting the hole location and class so we can define not only the class but also defined the target position for dropping the object. Some techniques that could be useful for this purpose include R-CNN, Faster R-CNN, Single Shot Multibox Detector (SSD), Singe Shot Refinement Neural Network (RefineDet), and You Only Look Once (YOLO).

Another limitations involve that the process of printing has to be interrupted, which means that the robot printer is not currently printing in the walls that are already moving in the conveyors which in a more real scenario both the robot printer and the cobot should be work in coordination in the same wall which present the challenge of coordination in time and space.

This time the cobot was defined as a fixed robot but this robotic arm could be mounted into a move base robot so instead of having the printed pieces mounted in a conveyor the robot assistant could be moving to different printing stations helping multiple printers to place the corresponding elements. Also, this approach will be more suitable in the case of on-site 3DCP projects.

In this case the vision sensing approach involves having a camera that is fixed in an ortho view to the 3D printed pieces. This is not an idea since it involves having the printed pieces mounted into a conveyor path. A more realistic approach will involve having the camera mounted close to the wrist or end effector of the RA mounted into a move base robot.

In this case the 3D printed walls are predefined in a very regular and straight shapes but one advantage of 3DCP technology is the design freedom which involves having intricate geometry's which would complicate relying solely on a vision sensing system, and a more robust system that involves data fusion from multiple sensors might be needed.

Conclusion

Traditional construction methods are very time-intensive and require heavy manual labor. The development of 3DCP solves many of these issues by automating the process but brings in a few of its own challenges. These threaten the efficiency and safety of the automation process and thus present a large market gap that needs to be bridged. Specifically, various tasks require further attention to fully automate such as plumbing, installing electrical boxes, adding steel reinforcements, placing windows, etc.

The proposed research leverages a collaborative robot (Cobot) to address this challenge. The Cobot would utilize machine vision to identify and pick the appropriate parts from a dispenser and place them into the appropriate gaps of a 3D-printed wall, eliminating the need for manual intervention and core drilling. This approach can streamline the 3DCP process, improve safety, and contribute to the wider adoption of this innovative construction technology.

Contributor Acknowledgements

Jorge Rojas was in charge of implementing the environment in CoppeliaSim, the implementation of the camera, sensors scripts, and child scripts for the pick and place algorithm involving the block-out feeder conveyor to the wall conveyor. The environment involves the robot printer, mounted extruder tool, ABB track external axis, toolpath planning for the robot printer, machine vision system for the camera blob, conveyor systems with proximity sensors, signal monitor to display different signals defined in the environment, and a UR10 with a child script for reading signals and executing the pick and place tasks.

Kunal Mamtani was in charge of training the deep learning model in an attempt to implement AI decision-making for the UR10 in placing the components into the corresponding hole shape in the walls. Kunal also created a classifier file to be used in the environment for integrating a feeder system, that feeds the three conveyors, to work with the UR10 assistant.

Agathiya Tharun was in charge of the evaluation and compilation of the findings. Agathiya also helped with refining the report, preparing the presentation, and integration attempts. Agathiya attempted to implement Kunal’s deep learning model into CoppeliaSim to fully automate the process of picking and placing the objects, however, the attempts were unsuccessful. Regardless, the M00 algorithm worked well enough, and thus the lack of a deep learning integration did not critically affect the project.

The team encountered challenges throughout the semester where two team members had dropped the class. This led to a constant redistribution of work and increased the difficulty of completing various tasks.

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